Confounded? Welfare Reform and the Earned Income Tax Credit in the 1990s

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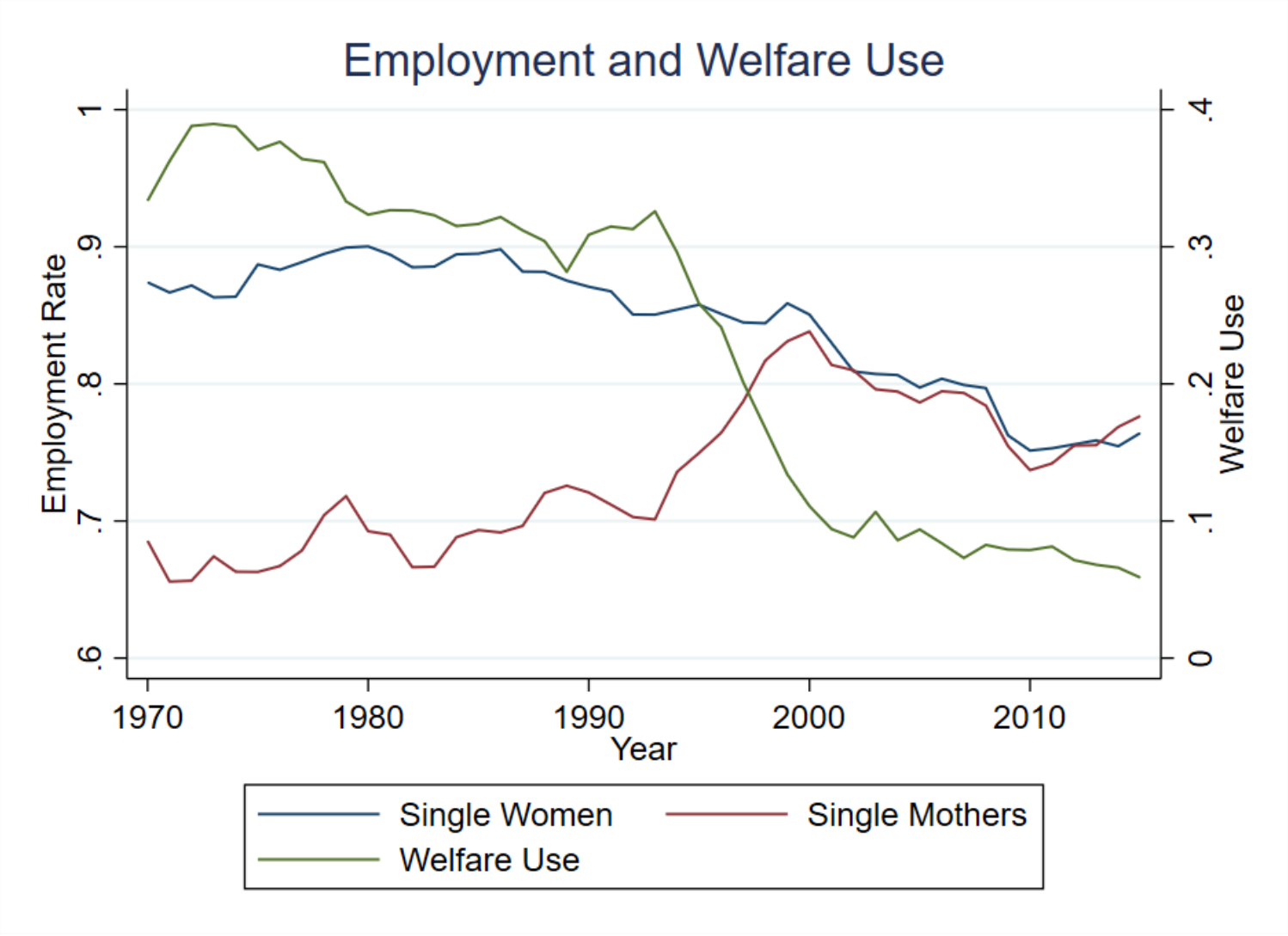
What caused the historic changes in employment in 1990s?



Start of a revolution in U.S. safety net

- Large literature credits the Earned Income Tax Credit for increases labor supply and reductions in welfare use in the 1990s
  - The 1993 expansion is a key piece of evidence of the EITC's labor supply effects
  - And to evidence of EITC's effects on many other outcomes
- Caused a revolution: "virtually all gains in spending…to families with earnings…" (Hoynes and Whitmore Schanzenbach 2015)
- Premised by view that it was the "carrots" rather than the "sticks".
- Twenty-five years later we are reconsidering cash assistance:
  - Paid family leave, large child tax credits, UBI, expanded UI

Concern: Estimates of 1993 EITC are "confounded" by welfare reform

- Ethnographic narrative credits bureaucratic barriers and social norms.
- EITC literature careful to control for welfare policies.
- Renewed debate whether cause was welfare reform or EITC (Kleven 2024).
  - But few econometric tools to resolve his dispute.

Is the estimated effect of EITC confounded?

- Falsification tests:

  (1) Use placebo tests to identify omitted variables bias

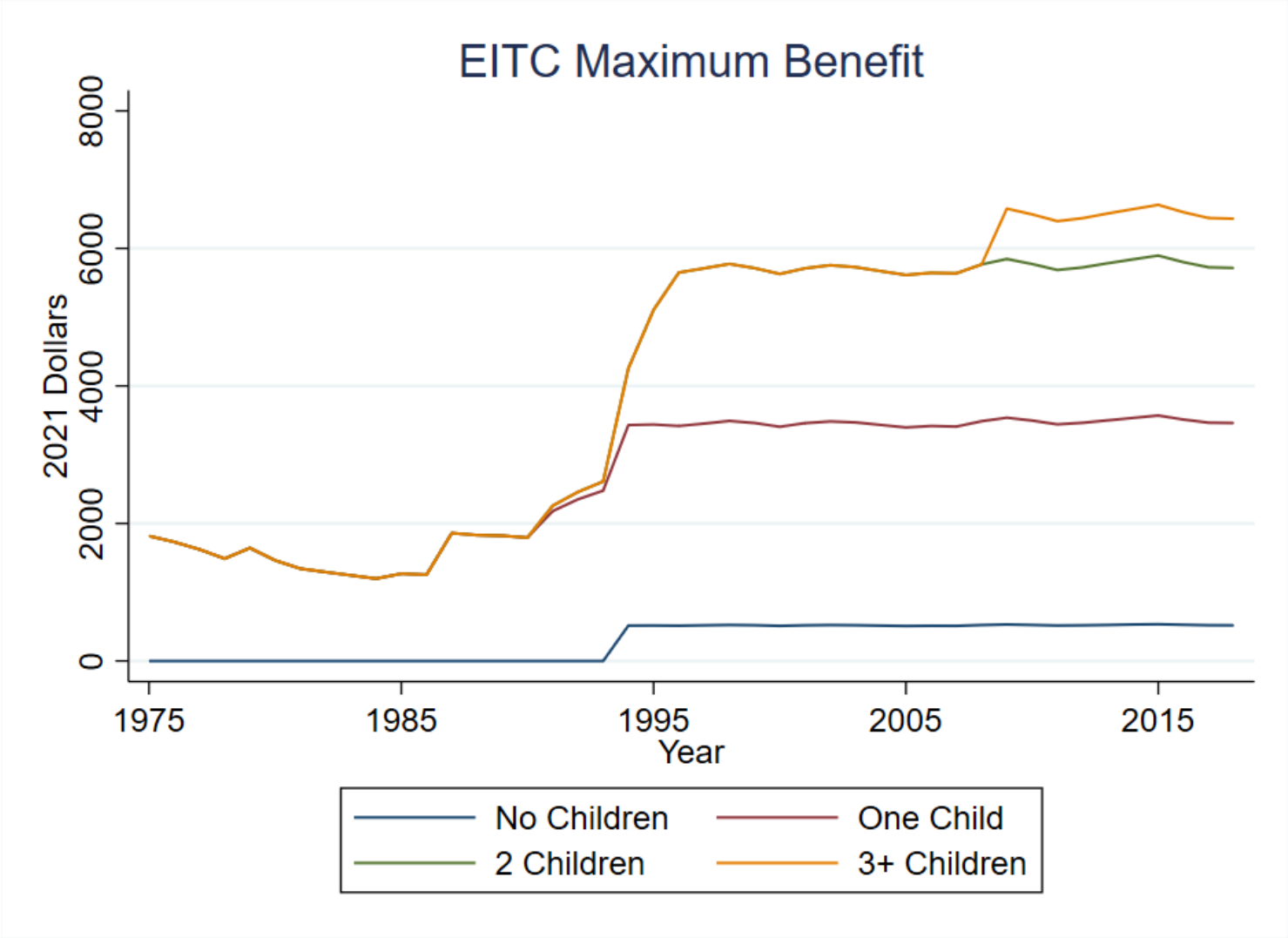
  (2) Test for “non-parallel trends” arising from differences in composition

- Results suggest identifying assumptions fail to hold, and estimated effects of 1993 EITC in DiD estimators is spurious.

- Estimates that control for confounding effect suggest little effect of EITC.

- Note: ML covariate selection would have gotten to same place.

Refresher: 1990s EITC expansion by # of kids



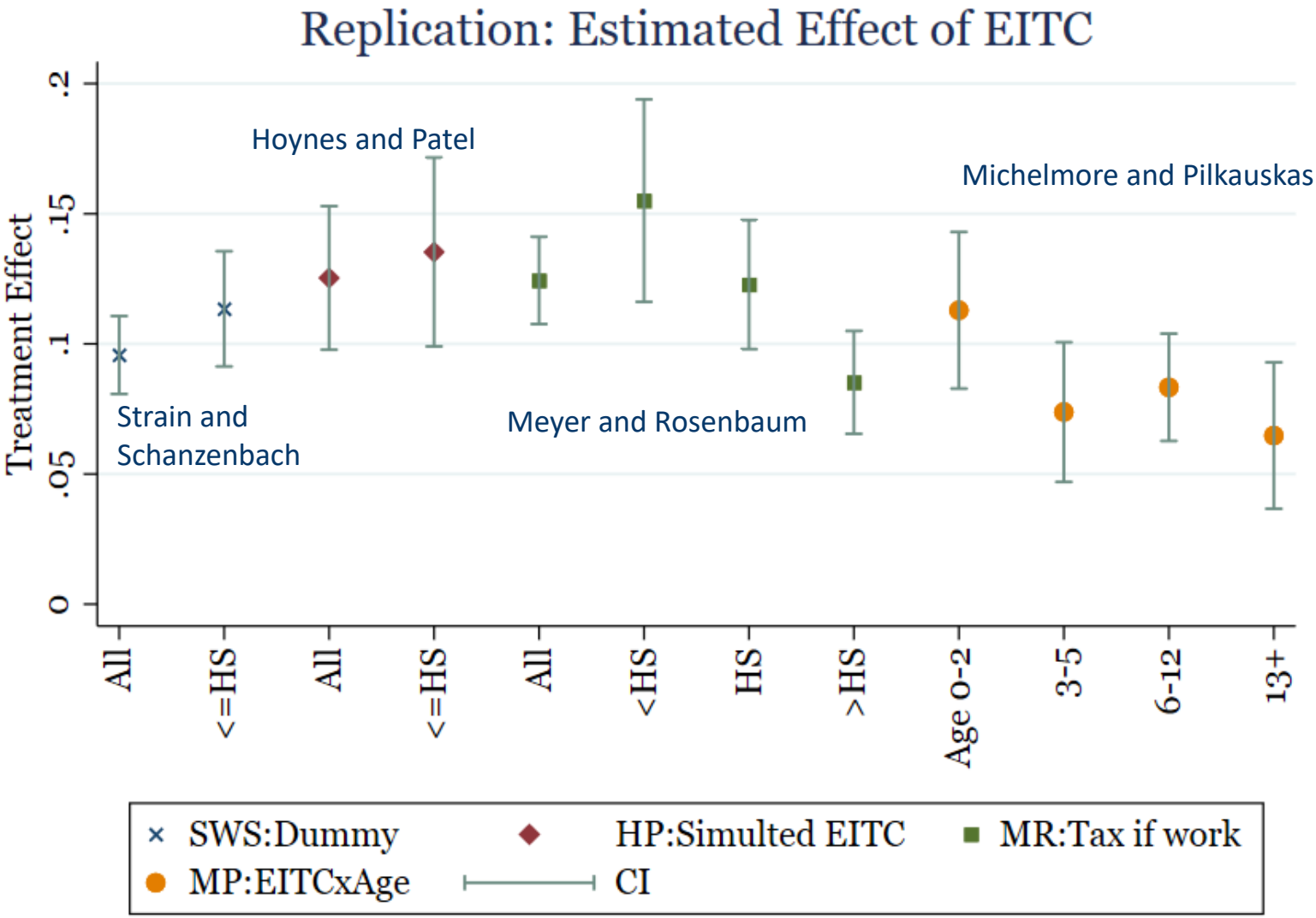
Difference-in-difference estimates of the EITC

- Literature based on difference-in-difference estimators:

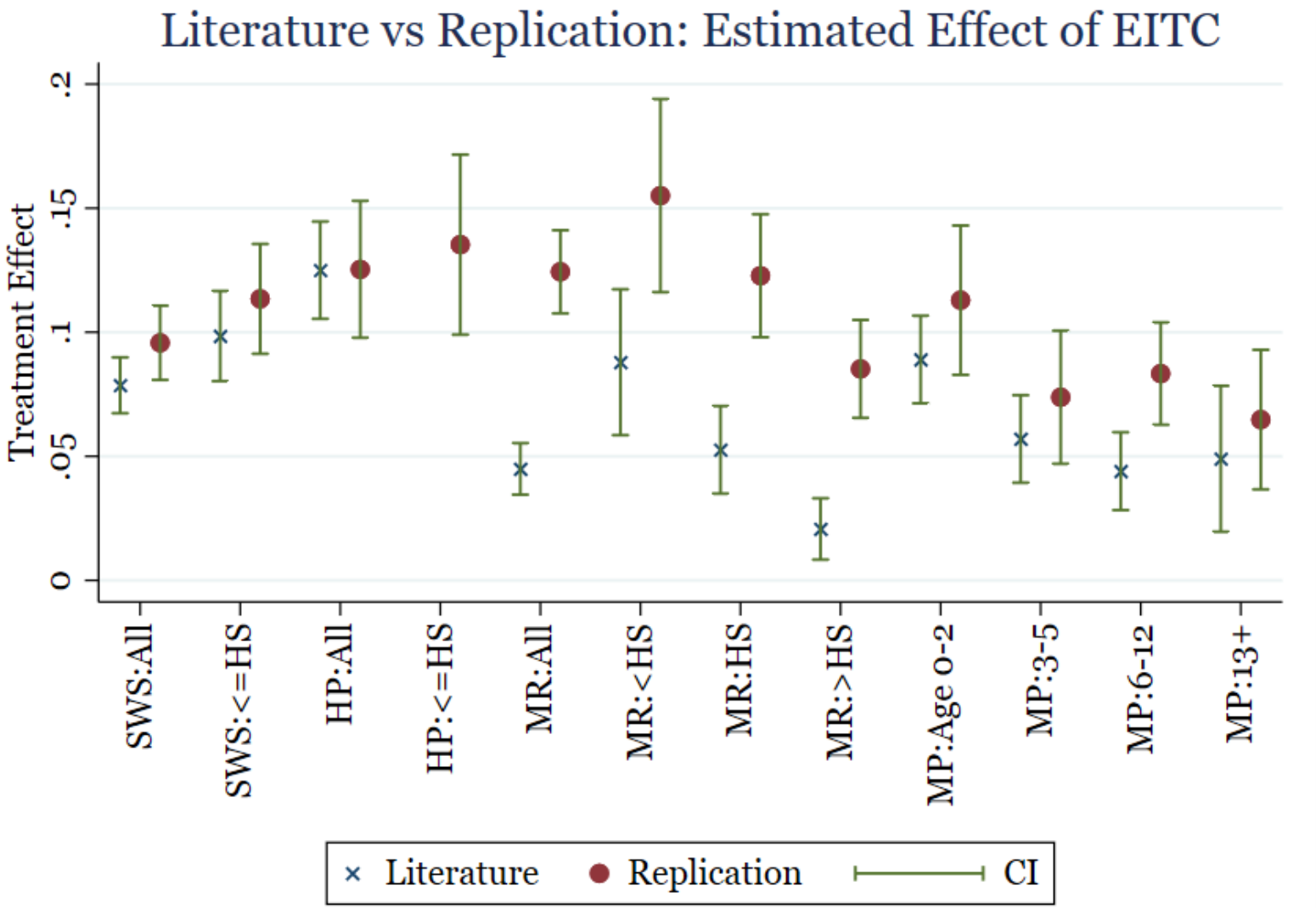
$$y_{it} = \beta_0 + \beta_1 after_t + \beta_2 treat_i + \beta_3 (treat_i * after_t) + X\beta + \varepsilon_{it}$$

- β_3 is effect of EITC on mothers of 2+ kids, after EITC expansion, compared to mothers of 1 child and/or childless women.
- Identifying assumption: "parallel trends."
- Assess robustness of this assumption by:
  - Test pre-trends; sequentially adding covariates; including e.g. state-by-year effects; excluding AFDC-waiver states…
  - There are no post-treatment tests of assumption.

DiD estimates: Large, significant effects of EITC



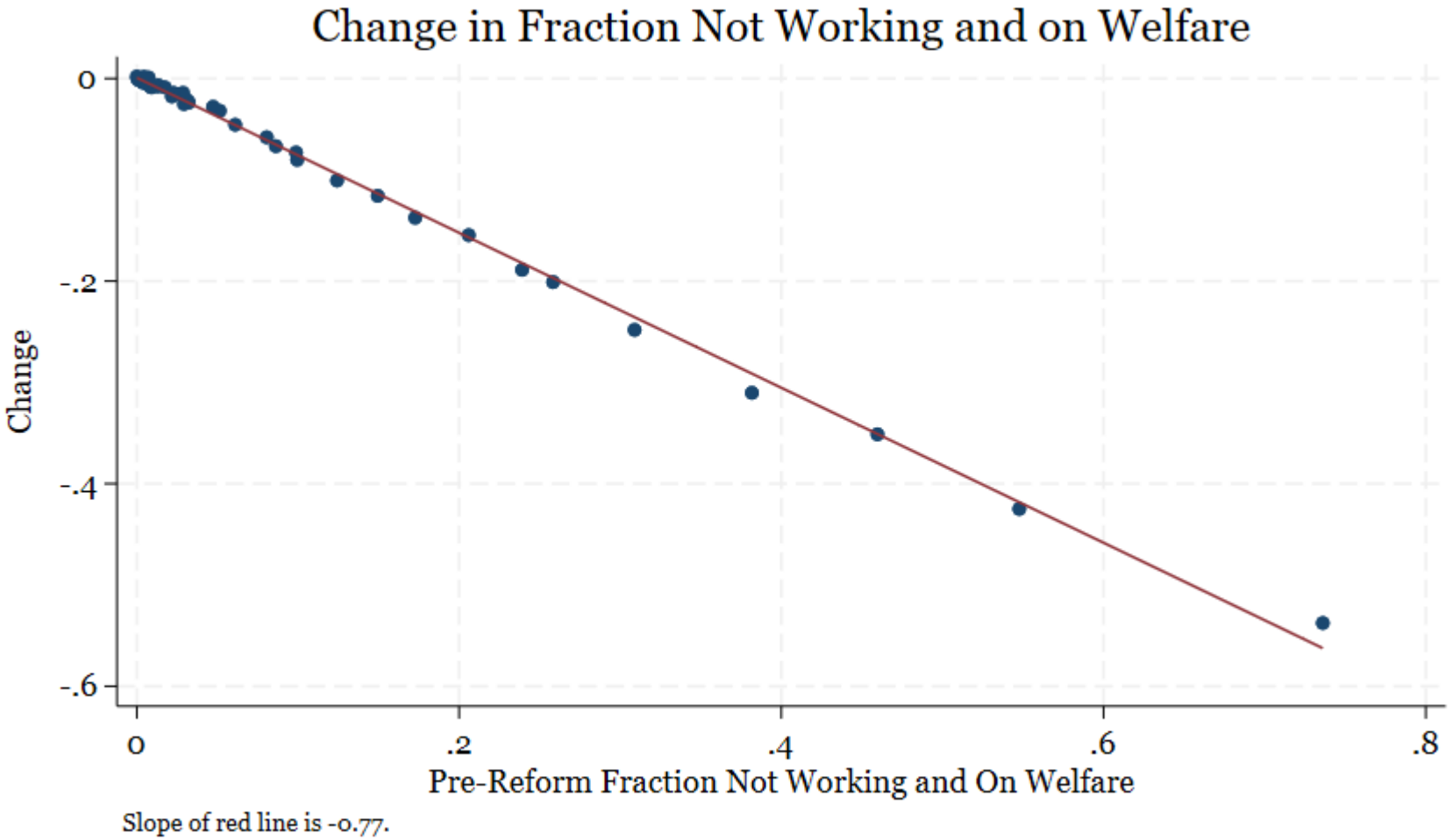
Closely match published estimates



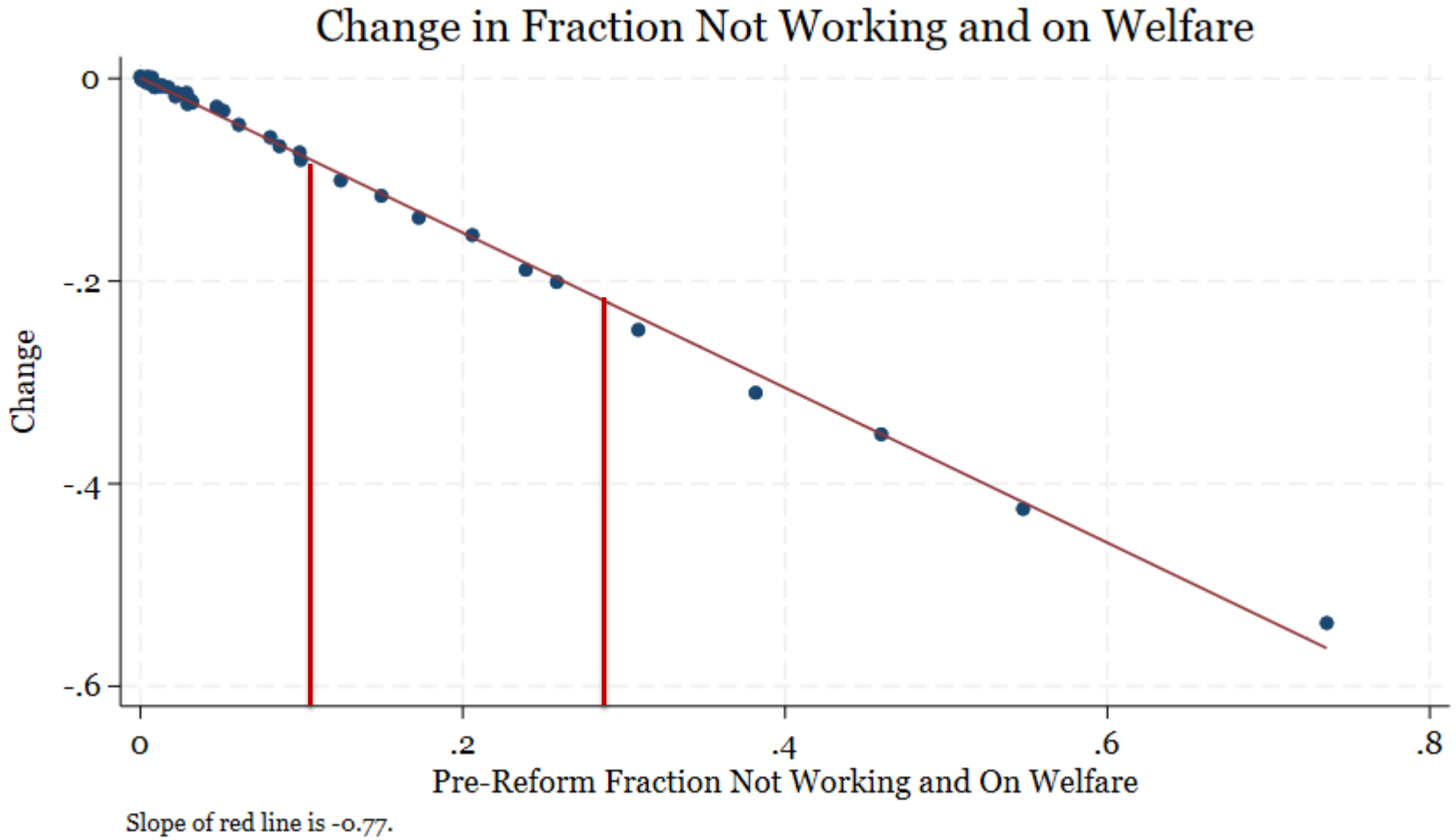
Alternative hypothesis: caseload reduction

- Ethnographic narrative credits bureaucratic barriers and social norms
  - "above all else, lower caseloads."
  - "it simply took a work requirement, strictly enforced."
- Quantitative predictions of this alternative hypothesis:
  - Welfare reform's "treatment effect" is proportional to pre-reform exposure to welfare/non-employment.

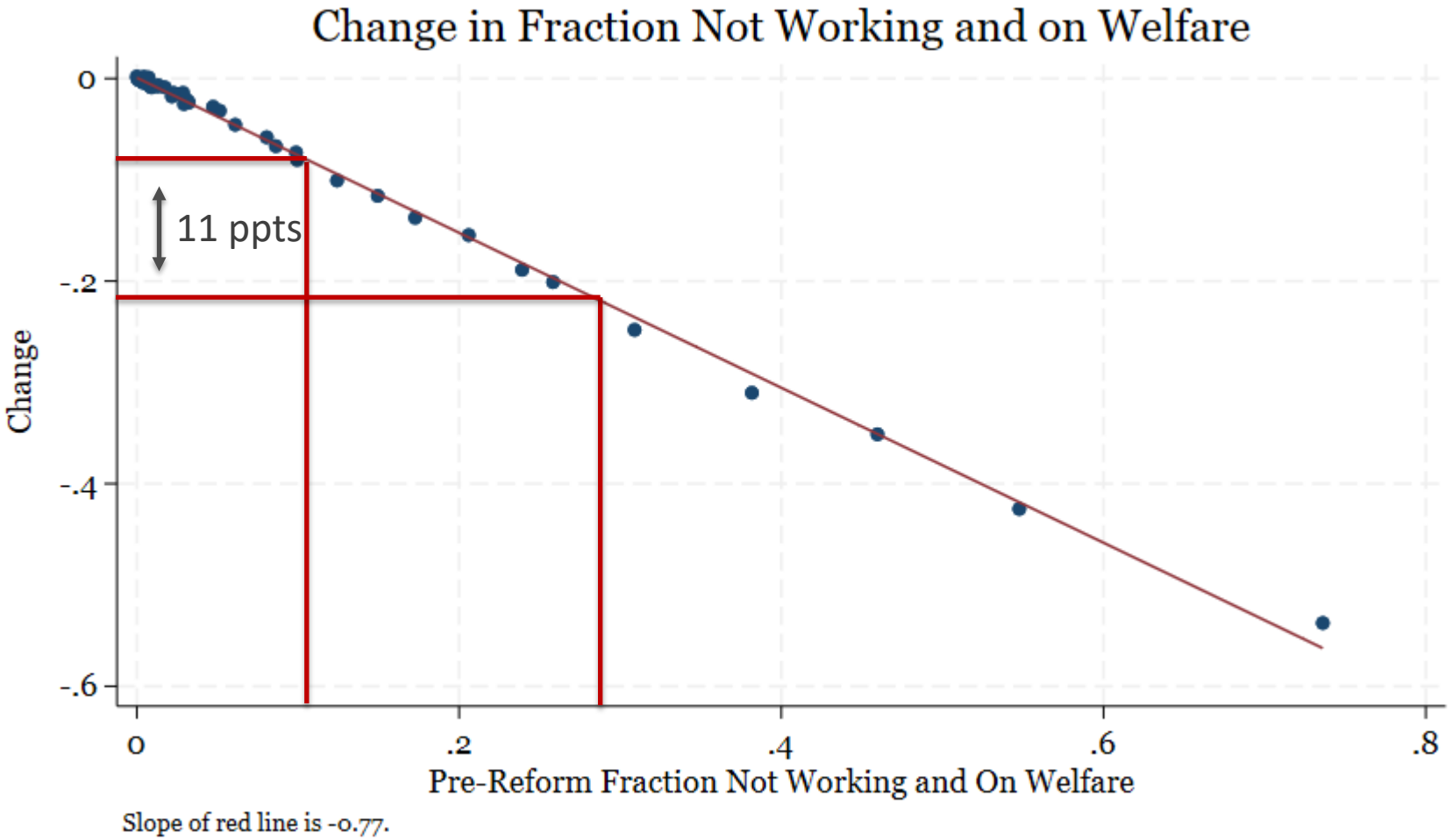
Caseload reduction back-of-the-envelope



Caseload reduction back-of-the-envelope



Caseload reduction back-of-the-envelope



Falsification test 1: Placebo DiD

- True model is

$$y_{it} = \beta_0 + \beta_1 after_t + \beta_2 treat_i + \beta_3 (treat_i * after_t) + \boldsymbol{\gamma_s Z_s after_t} + \varepsilon_{it}$$

- Assume Z_s is an omitted variable and $(treat_i * after_t)$ is a dummy variable. Then:

$$\hat{\beta} = \beta_3 + \gamma \frac{cov(treatment*after, Z)}{var(treatment*after)}$$

$$= \beta_3 + \gamma[E(Z|T=1) - E(Z|T=0)]$$

- Placebo test procedure:

(1) Estimate DiD in situations constructed such that β_3 is zero.

(2) Check if $\hat{\beta}$ correlated with differences in *Z* between groups.

Falsification test 2: “non-parallel trends”

Assume Z_s is a vector of dummy variables indexing subgroups (s) of treatment and control groups. ω_s^T is the weight of each subgroup in the treatment group:

Treatment effect (in 2x2 DiD) is:

$$\beta_3 = (Y_1^T - Y_0^T) - (Y_1^C - Y_0^C) = \Delta Y^T - \Delta Y^C = \sum \omega_s^T \Delta Y_s^T - \sum \omega_s^C \Delta Y_s^C$$

Adding and subtracting the change in the control’s subgroups outcomes weighted by the treatment subgroup weights ($\omega_s^T \Delta Y_s^C$) and rearranging gives the following decomposition:

$$\beta_3 = \sum \omega_s^T (\Delta Y_s^T - \Delta Y_s^C) + \sum (\omega_s^T - \omega_s^C) \Delta Y_s^C$$

Bias? Do within-group-trends predict across-group divergence in trends?

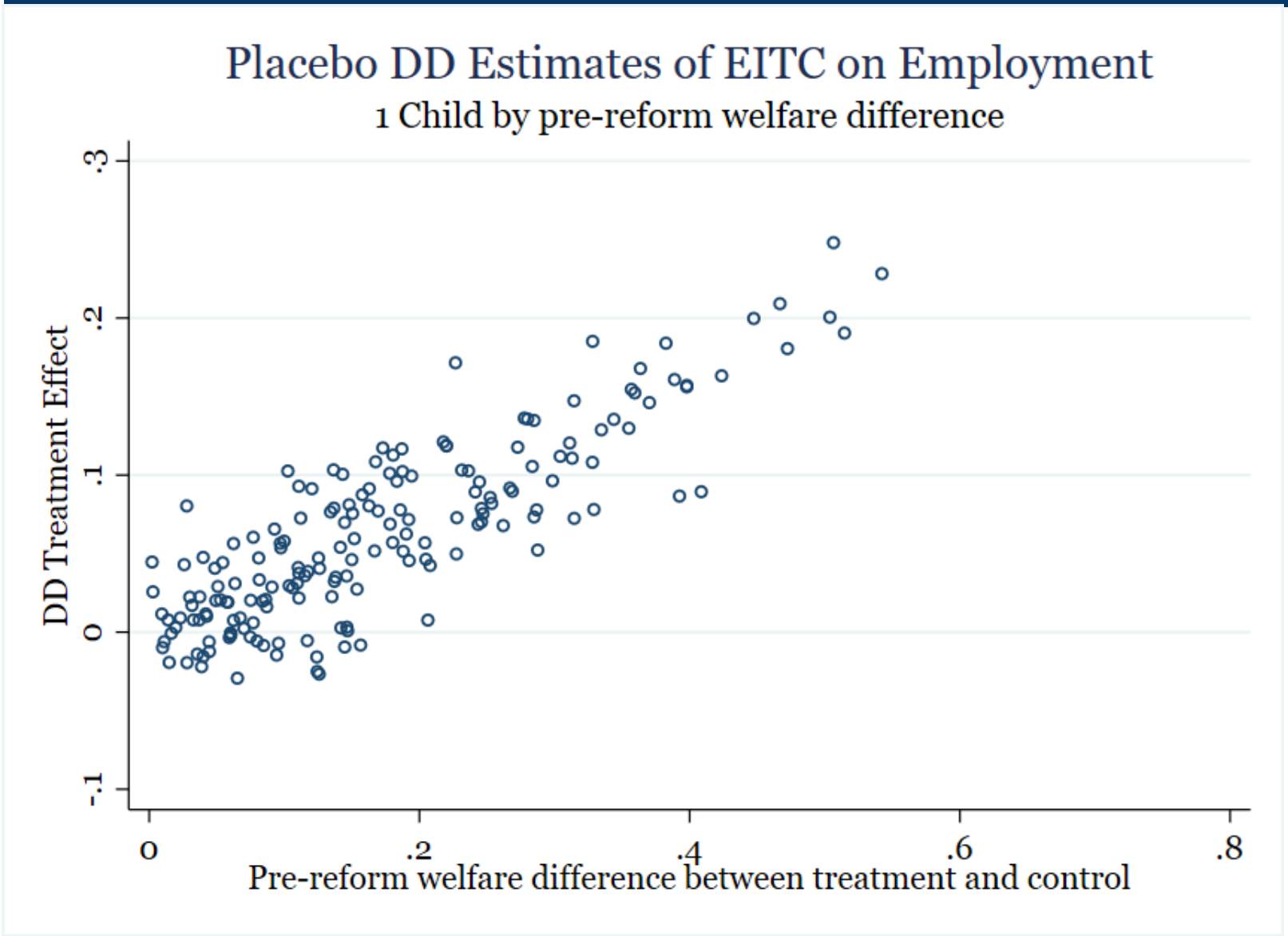
$$\beta_3 = \sum \omega_s^T (\Delta Y_s^T - \Delta Y_s^C) + \sum (\omega_s^T - \omega_s^C) \Delta Y_s^C$$

- First component is weighted sum of the "treatment effect" for each subgroup *s*.
  - Identified by across-group change in outcomes.
- Second component is the trend (or time effect) in control group scaled by differences in composition of treatment and control groups.
  - Contains no information on post-reform outcome of treatment group.
  - Identifying assumption is that this term is zero.

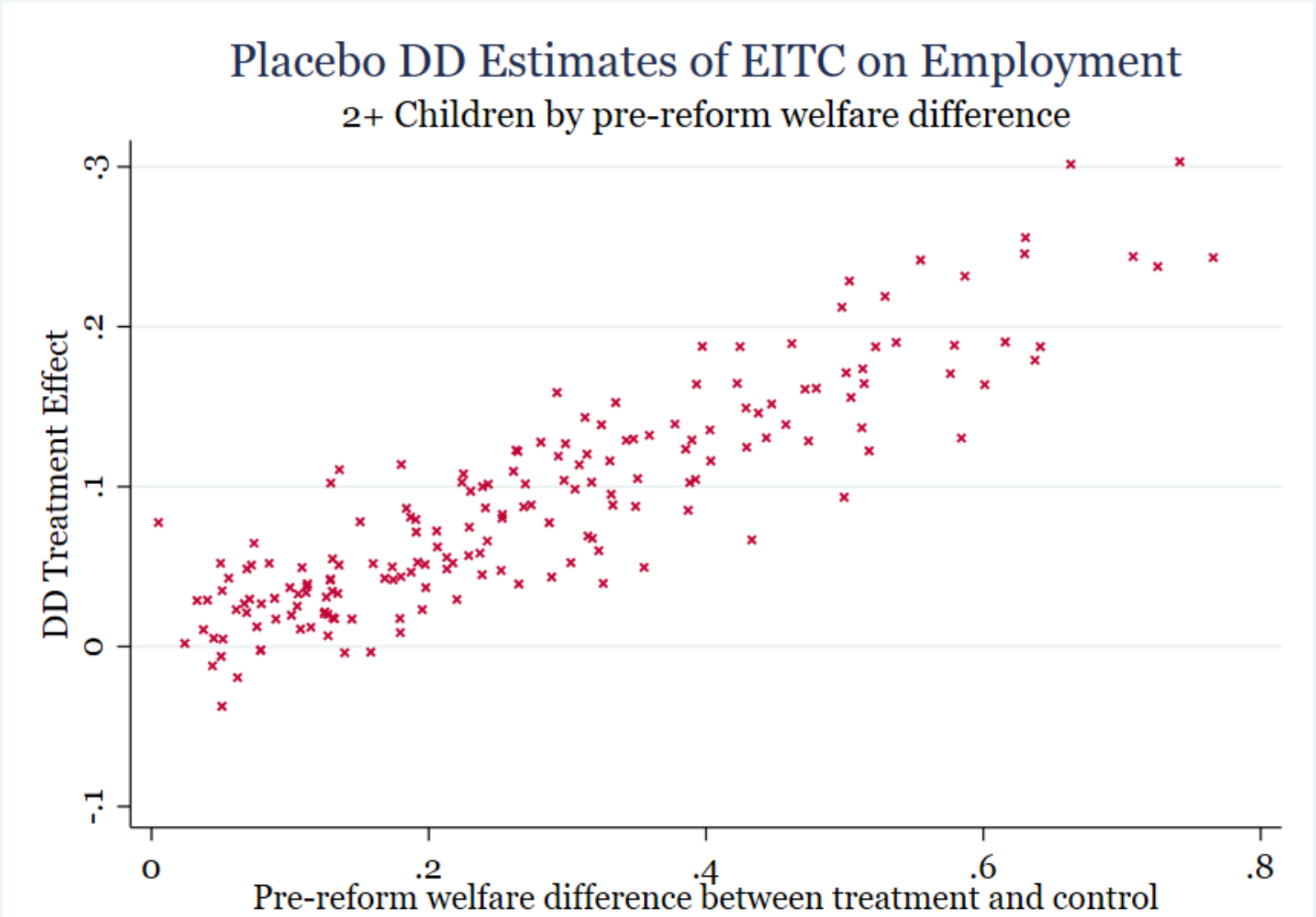
Placebo procedure

- Drop treatment group observations
- Divide control group observations into group and randomly assign placebo treatment status.
  - Assignment by demographics and/or propensity to work/use welfare
- Estimate DiD (with state*year effects, individual controls)
- Capture β^{hat} and mean difference in characteristics of groups: $\mathrm{E}(\mathrm{Z}|\mathrm{T}=1)-E(Z|T=0)$.

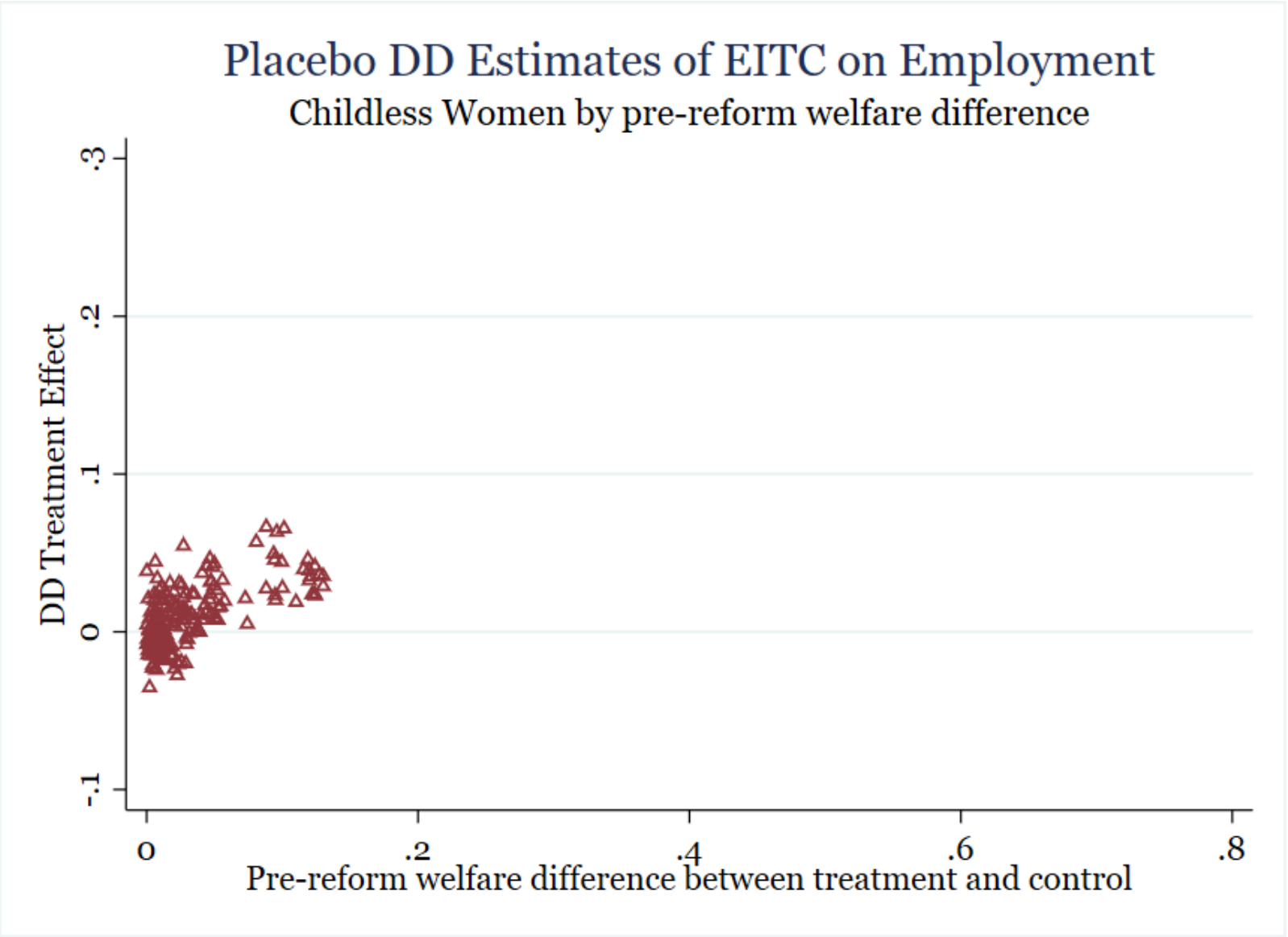
Placebo estimates are correlated with pre-reform welfare use (mothers of 1 child)



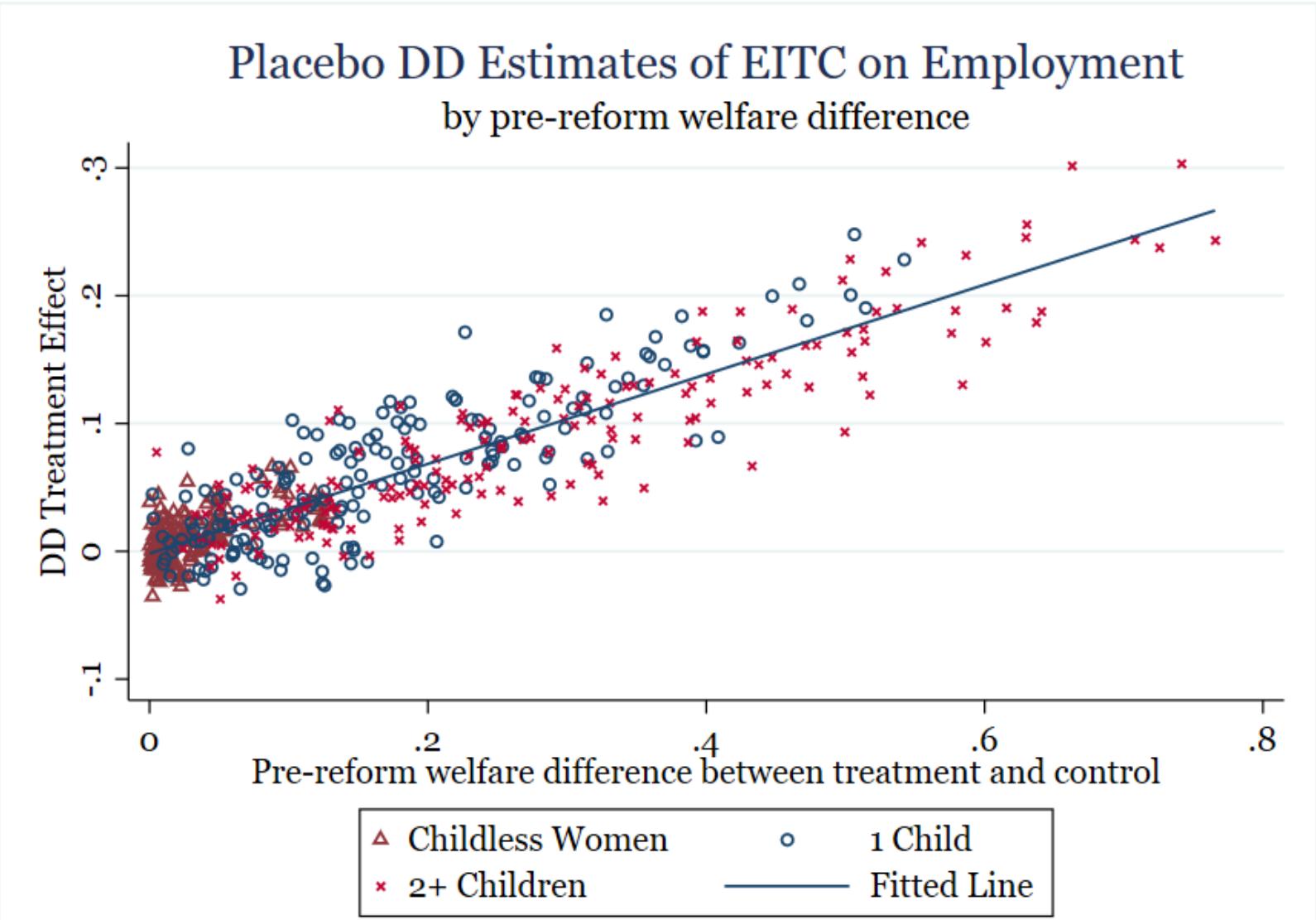
And within mothers of 2+ children



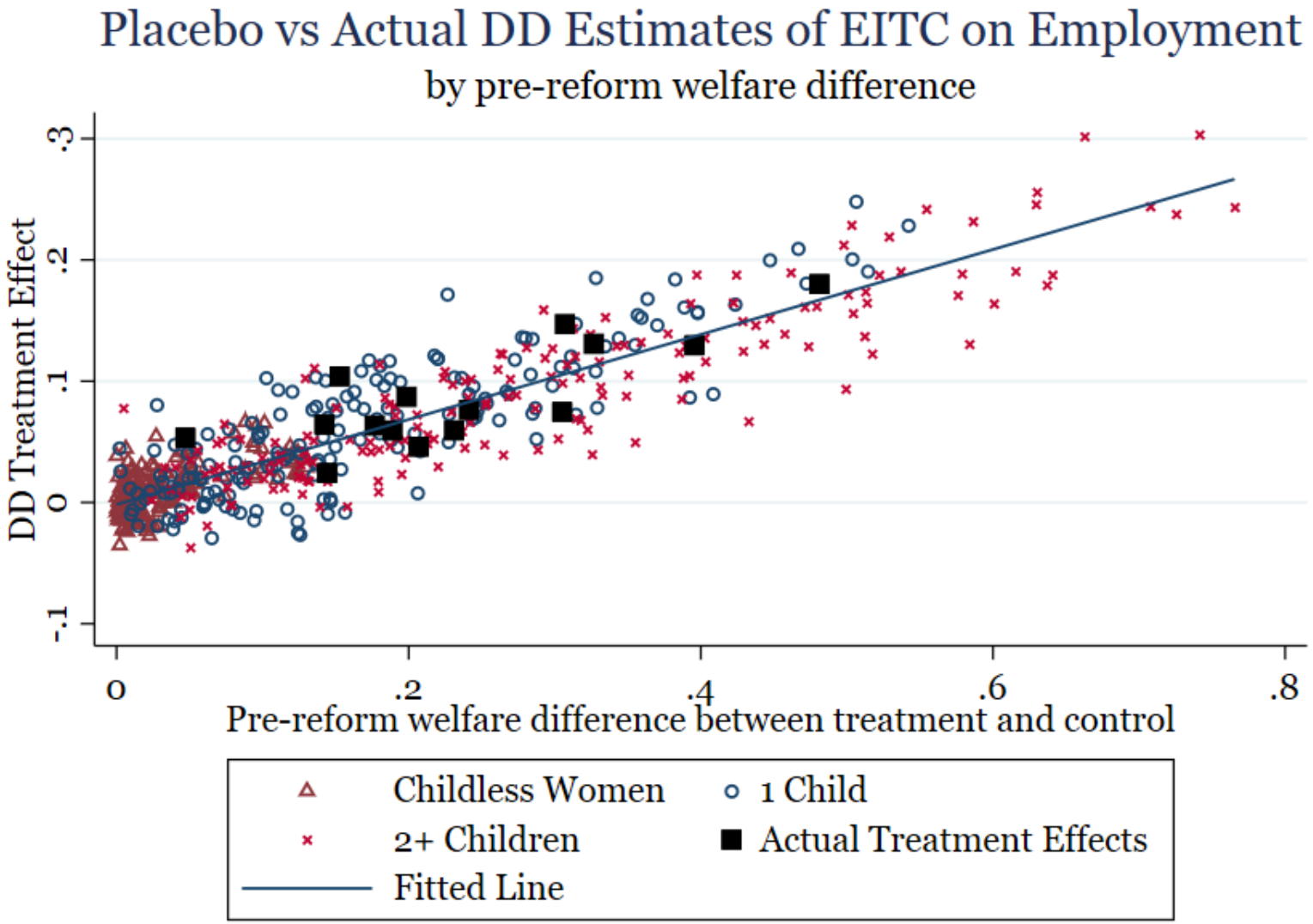
And even childless women



Same relationship between placebo estimates welfare use within all groups



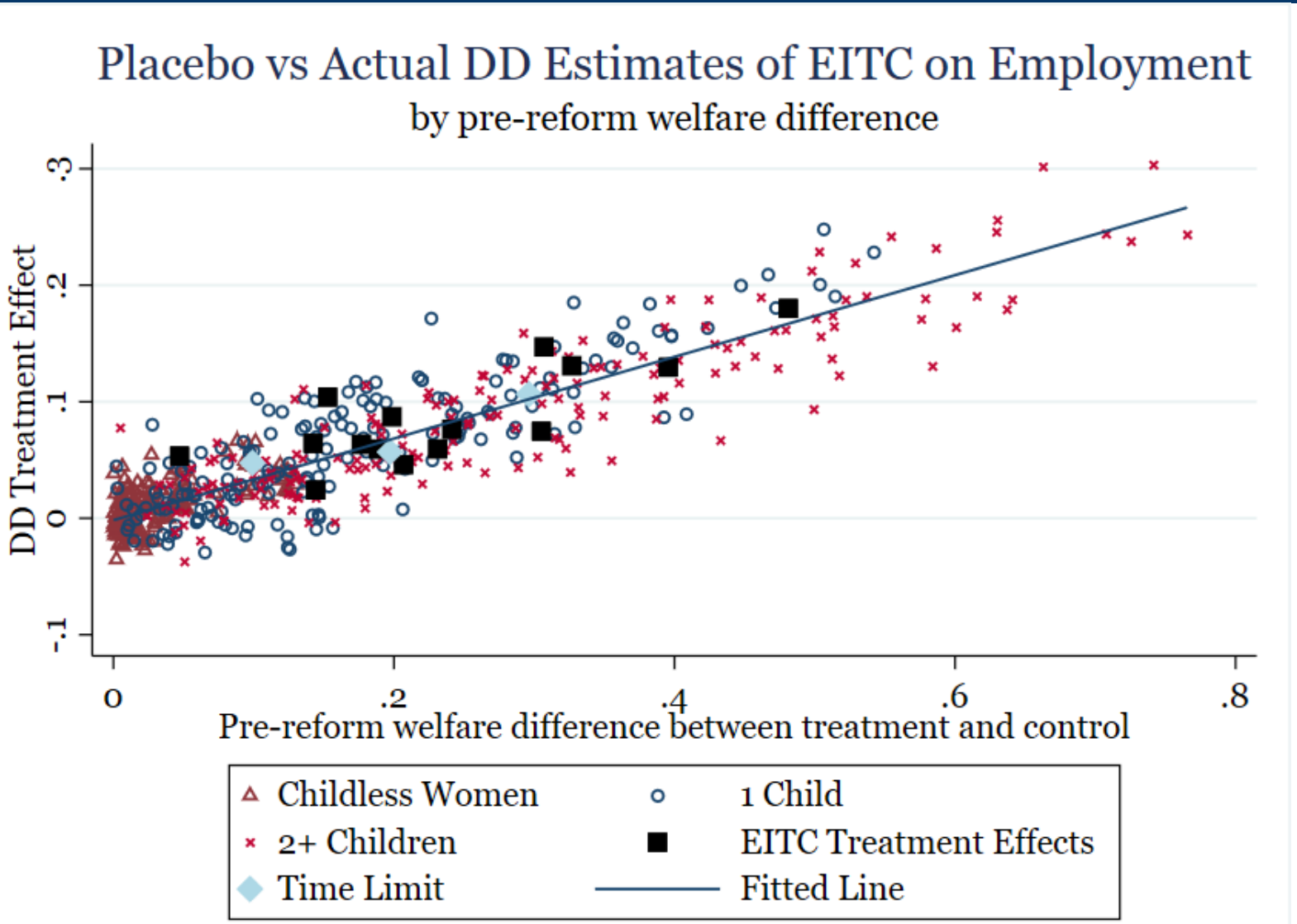
Placebo estimates exactly predict actual DiD coefficient estimates



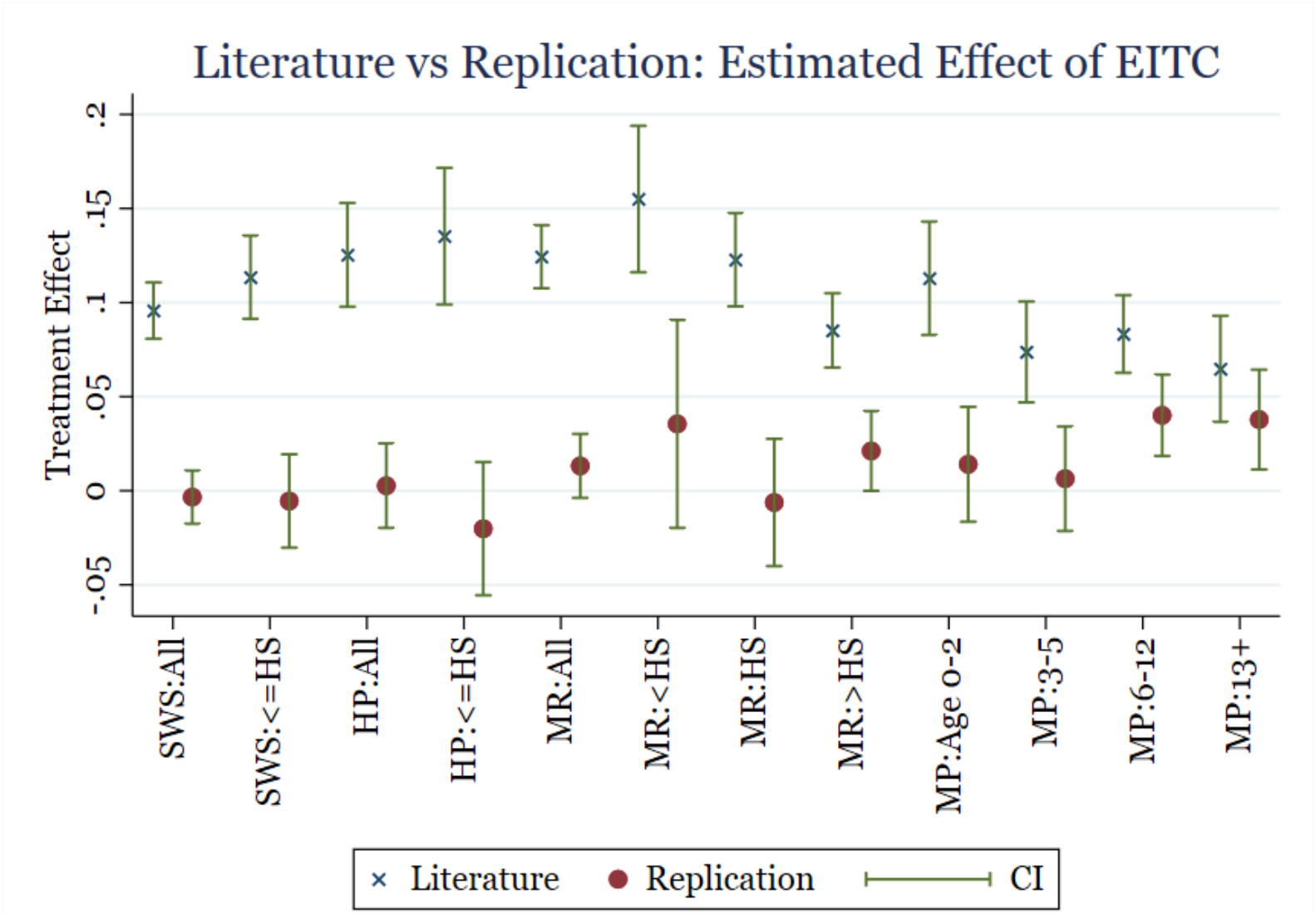
Digression: Welfare time limits

- Related literature (Grogger 2003, 2004): What was effect of 5-year cumulative time limit on welfare use and employment?
- Uses identical specification *except* treatment and control groups are totally different: based on age of youngest child.
- Finds large anticipatory effect of time limits.
- If the EITC is confounded, time limits should also be confounded by same source of bias.

Placebo estimates exactly predict actual EITC and time limit coefficient estimates



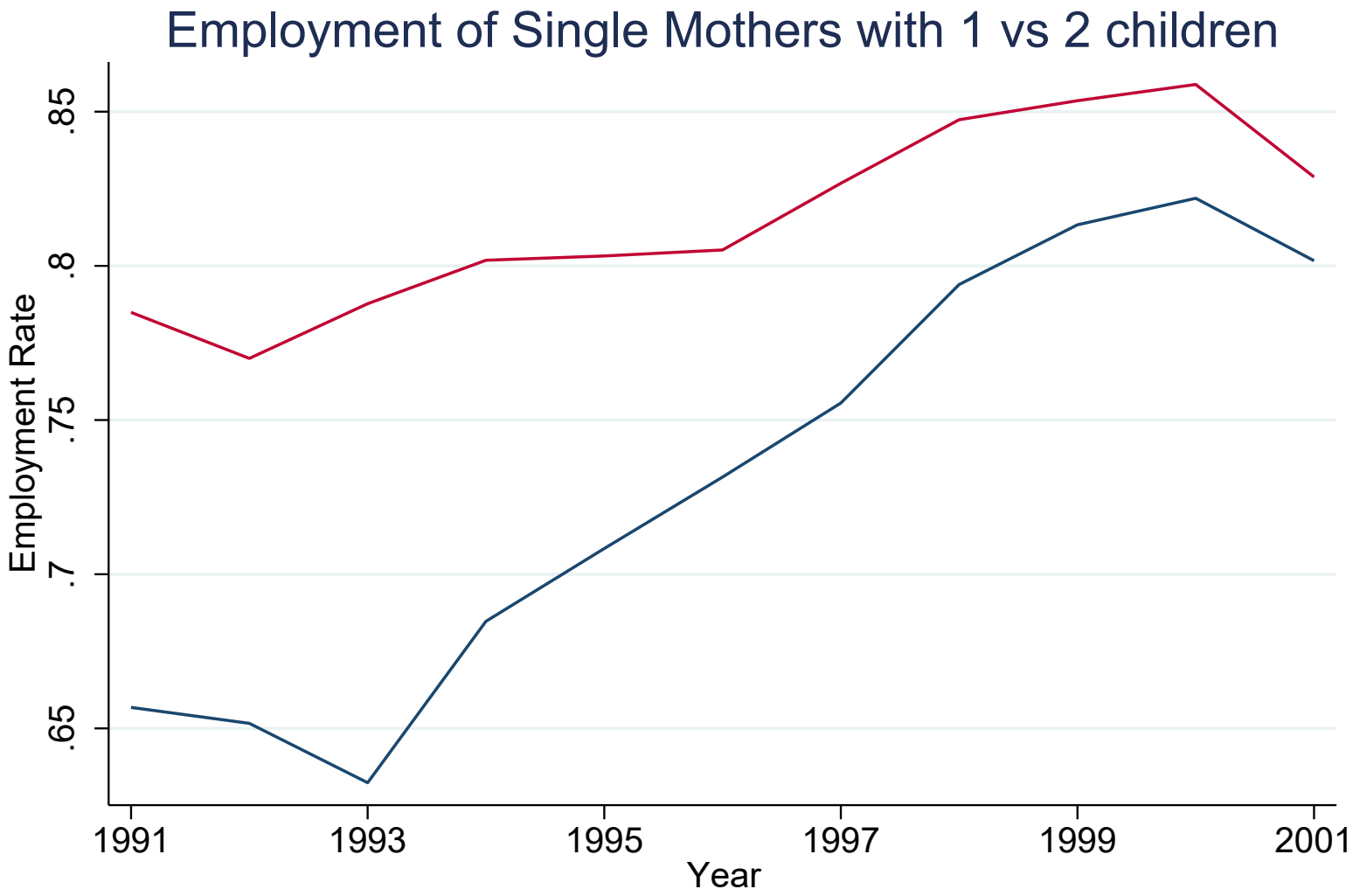
Control for time X welfare exposure: Effect of EITC on employment attenuated



Second test: Non-parallel trends?

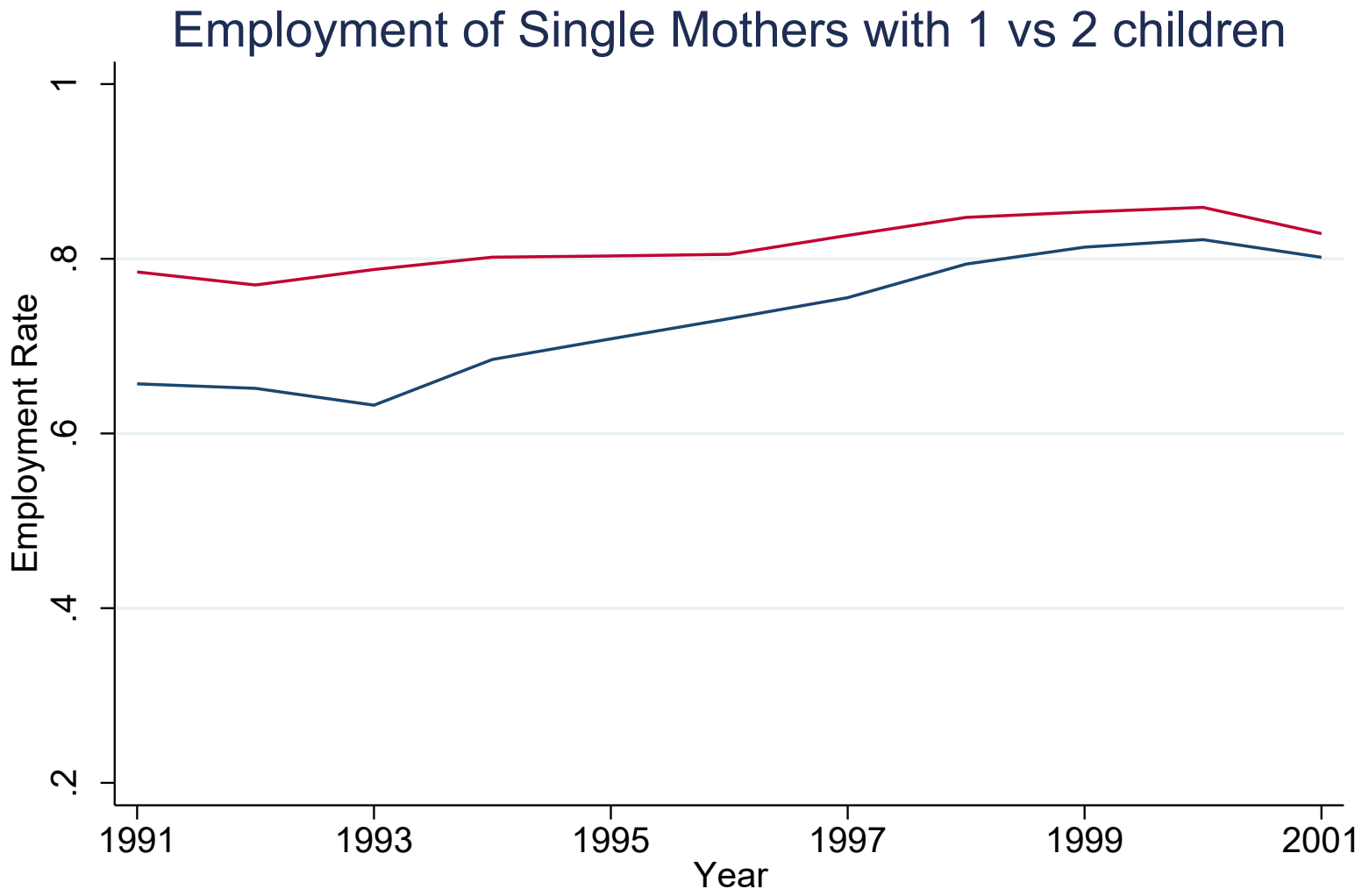
- Define subgroups (s) by quintiles of predicted pre-reform propensity to receive welfare
  - Form quintiles from prediction from probability model using demographic and family characteristics 1991-1993
  - Disaggregate treatment and control groups by subgroup
  - Assess relative weights and within-group trends

Graphical representation of DiD
2+ children (treatment) vs 1 child (control)



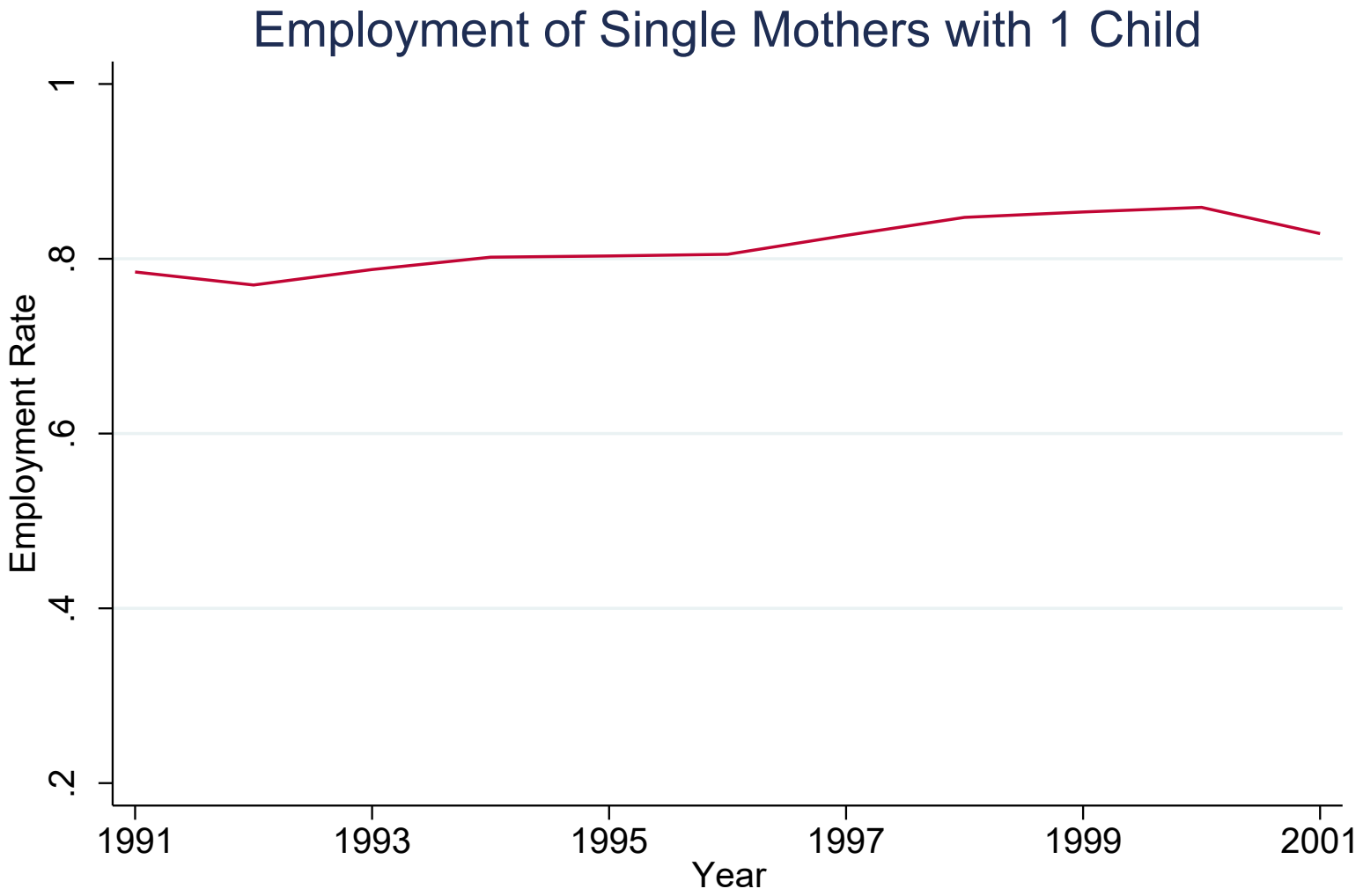
Source: March CPS. Mothers with 1 child in red, mothers of 2 children in blue.

(Change scale to illustrate decomposition)



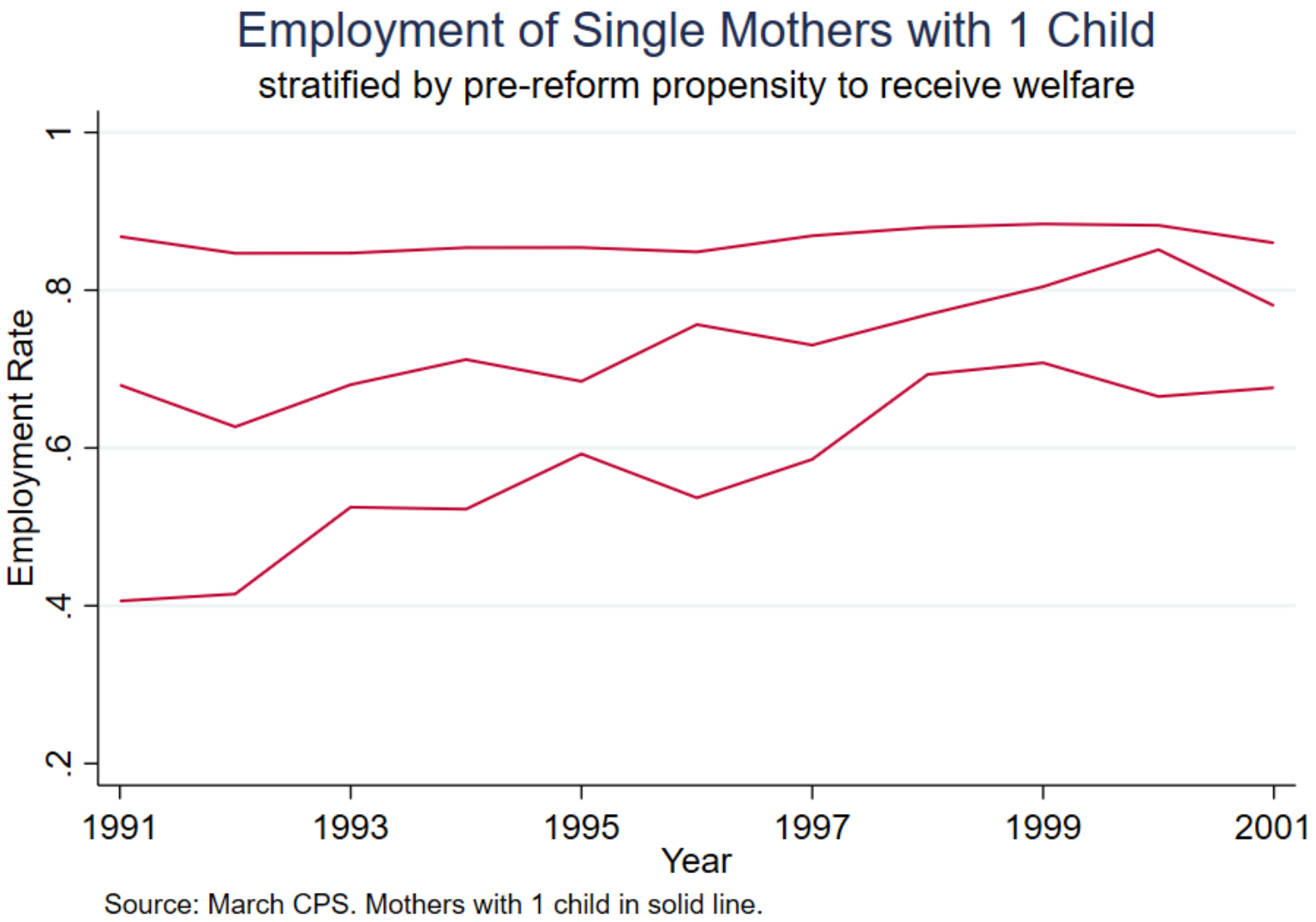
Source: March CPS. Mothers with 1 child in red, mothers of 2 children in blue.

Start with control group

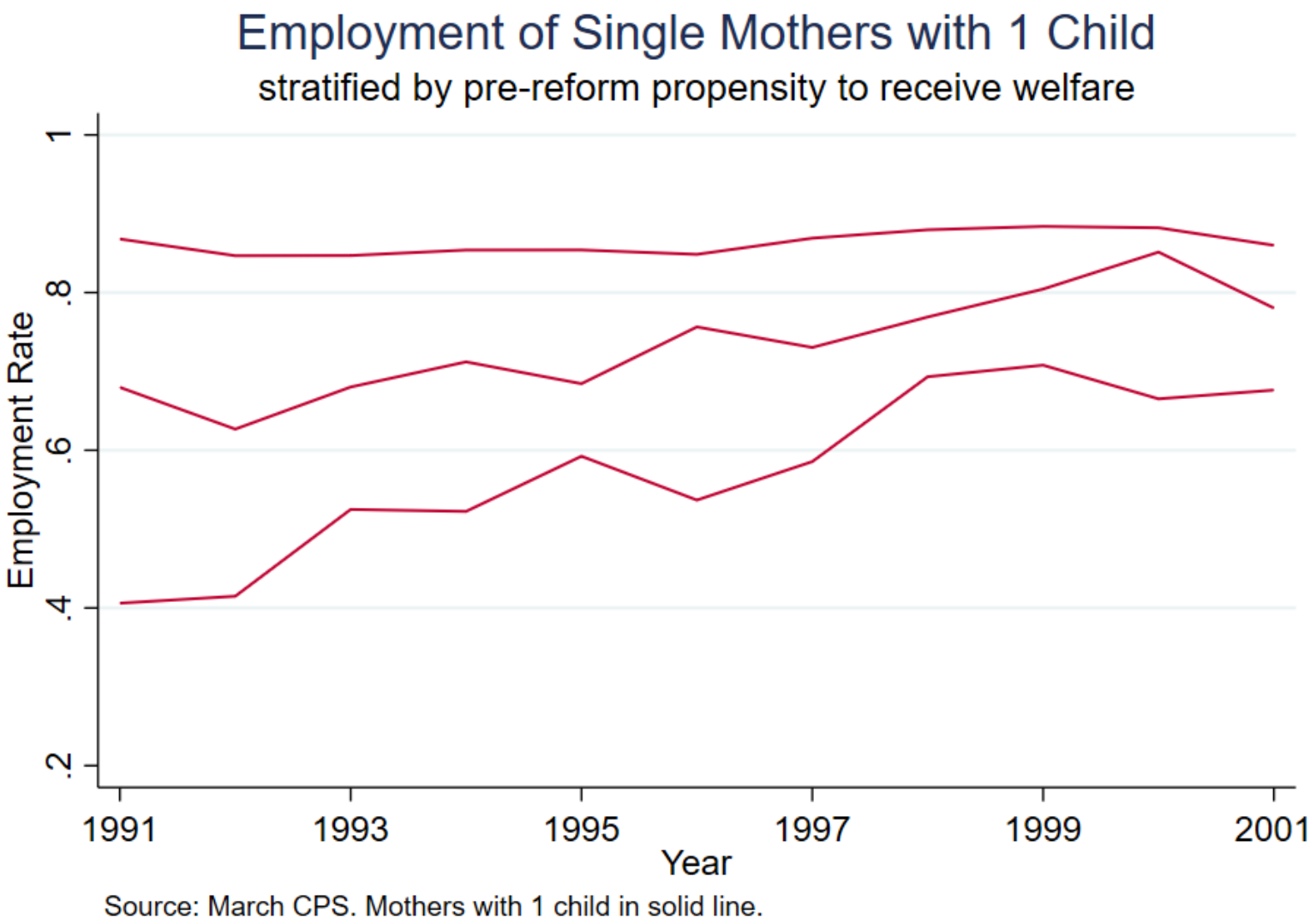


Source: March CPS. Mothers with 1 child in red.

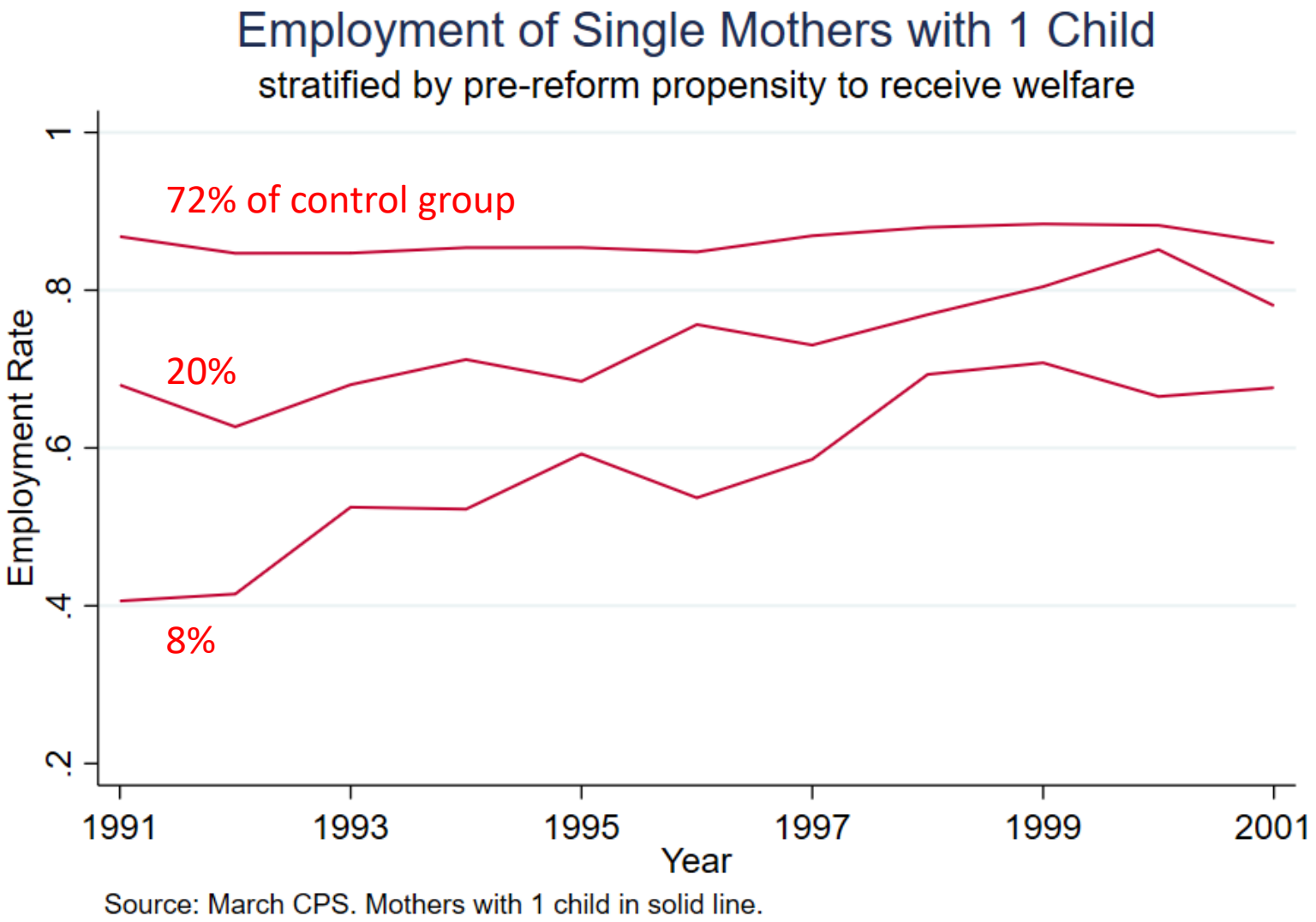
Stratify and disaggregate by pre-reform propensity-to-use-welfare quintile



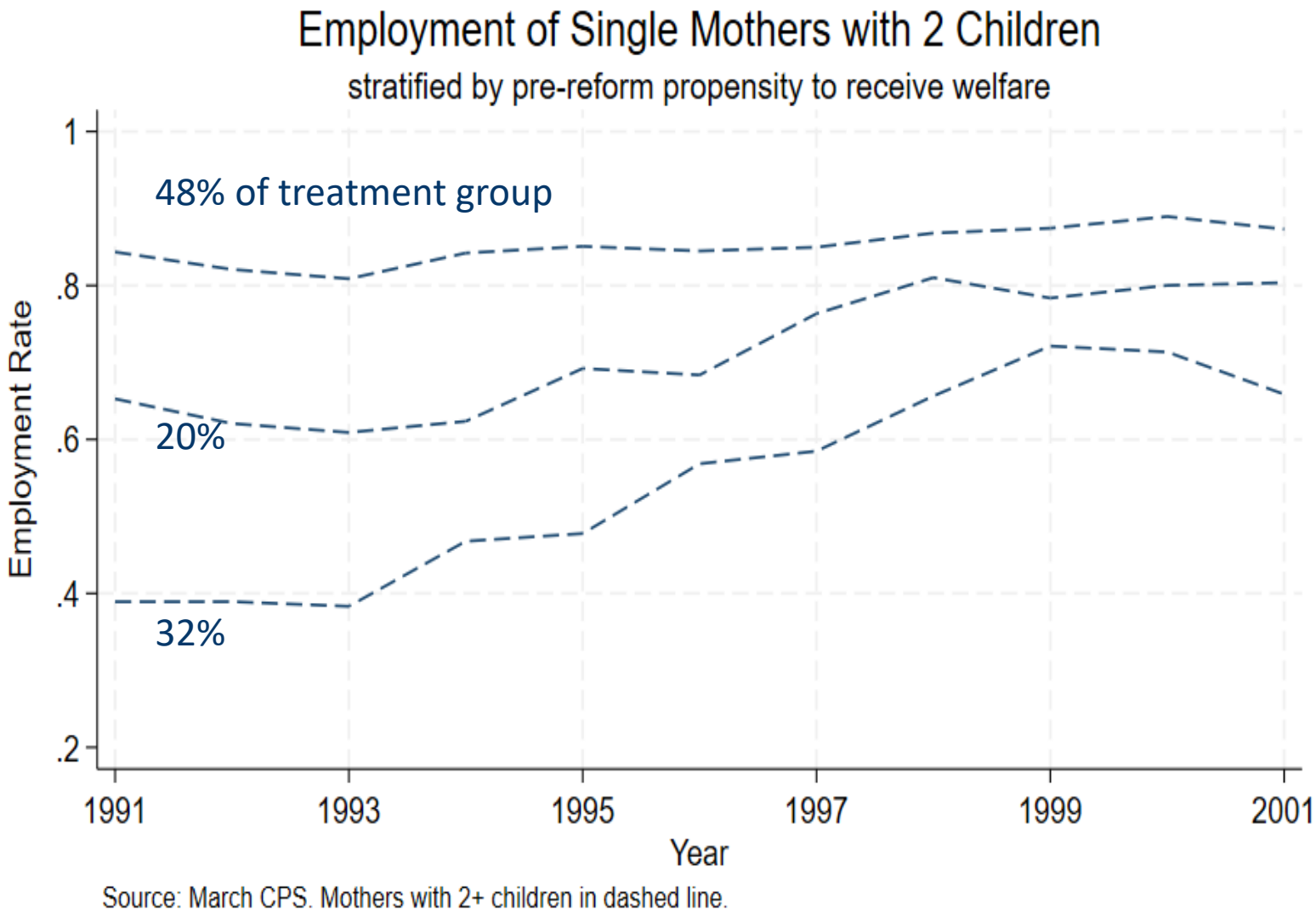
Are subgroup trends “parallel?” No.



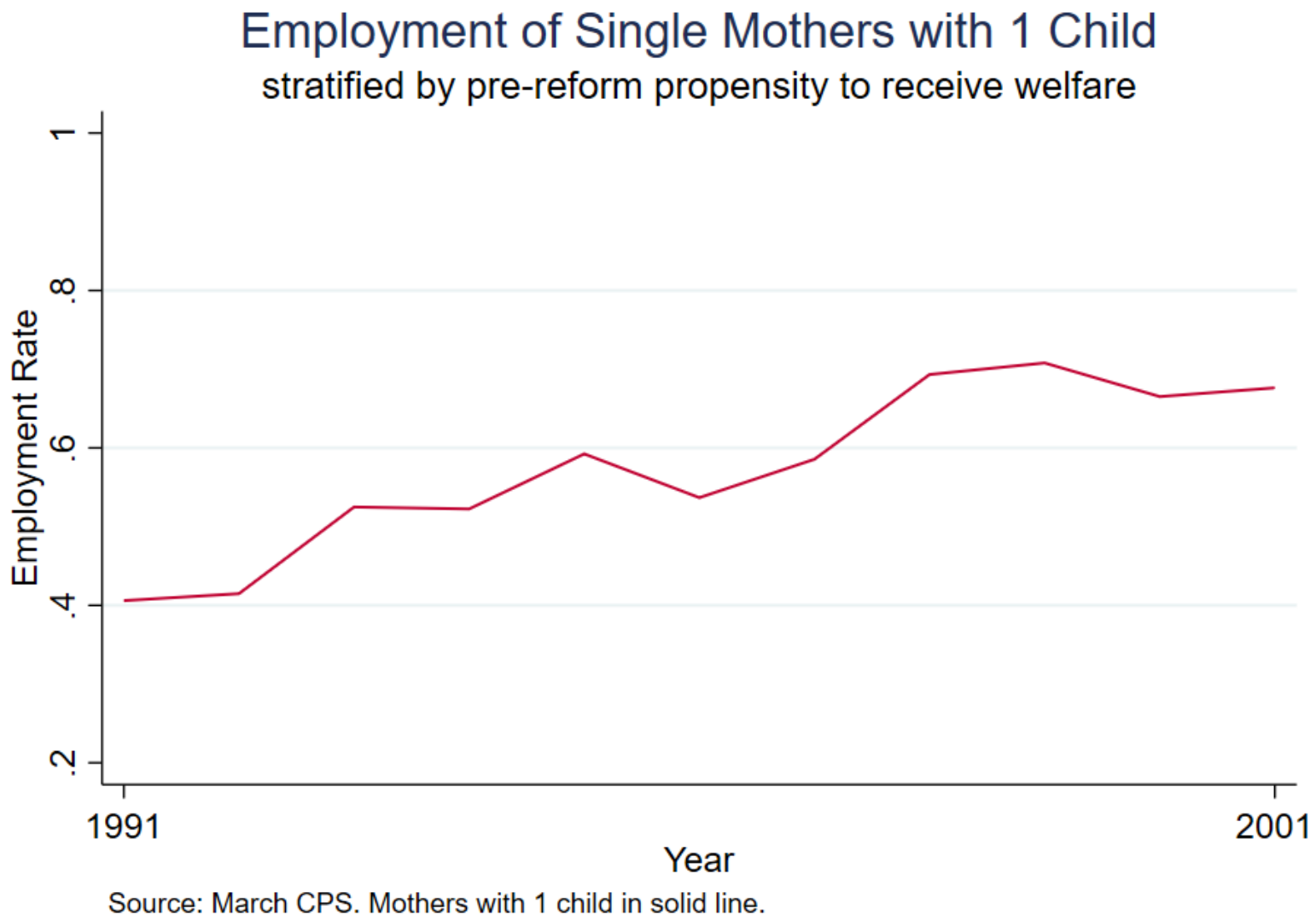
Are subgroup trends “parallel?” No. What is composition of treatment group?



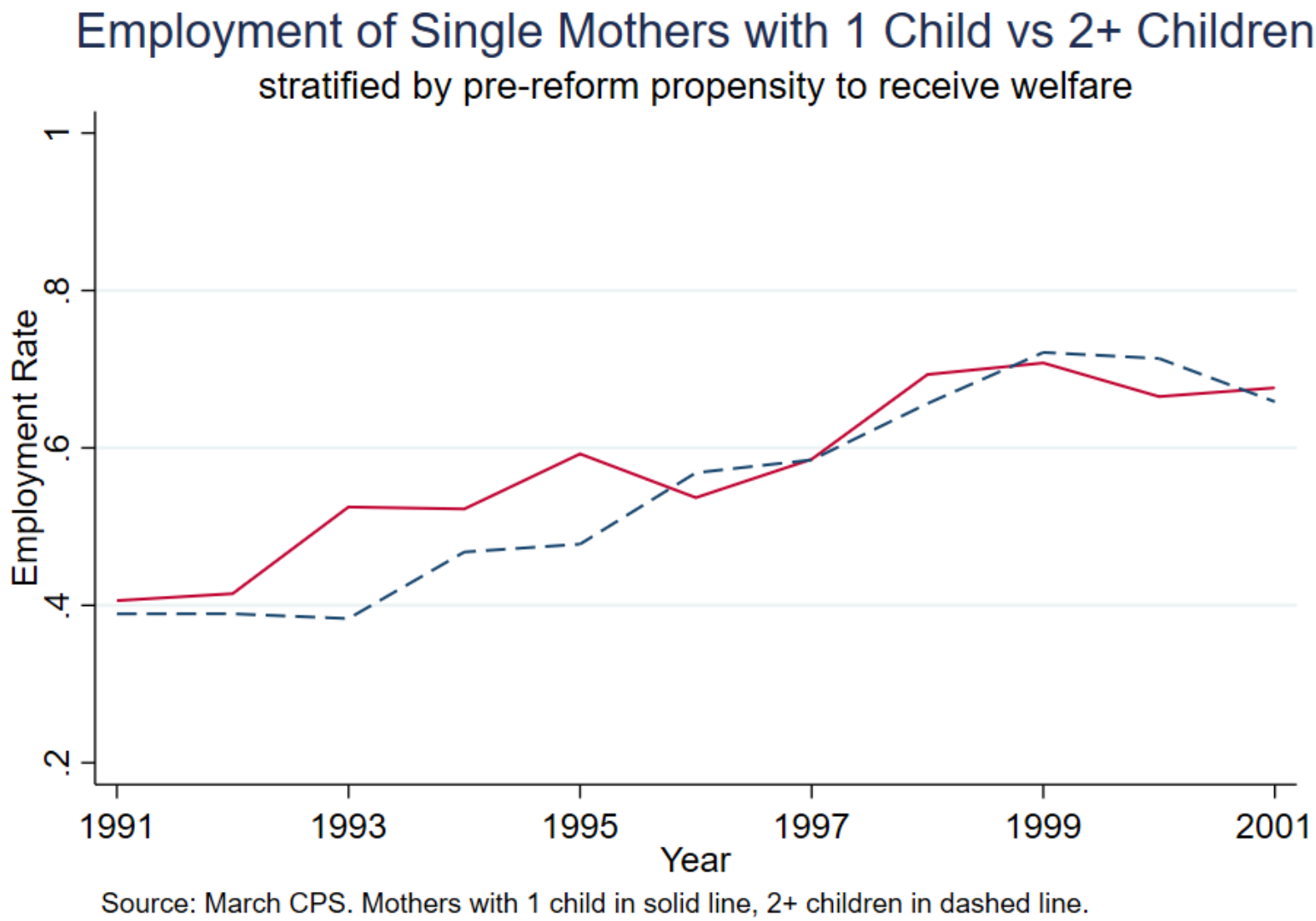
Are weights within treatment and control the same? No.



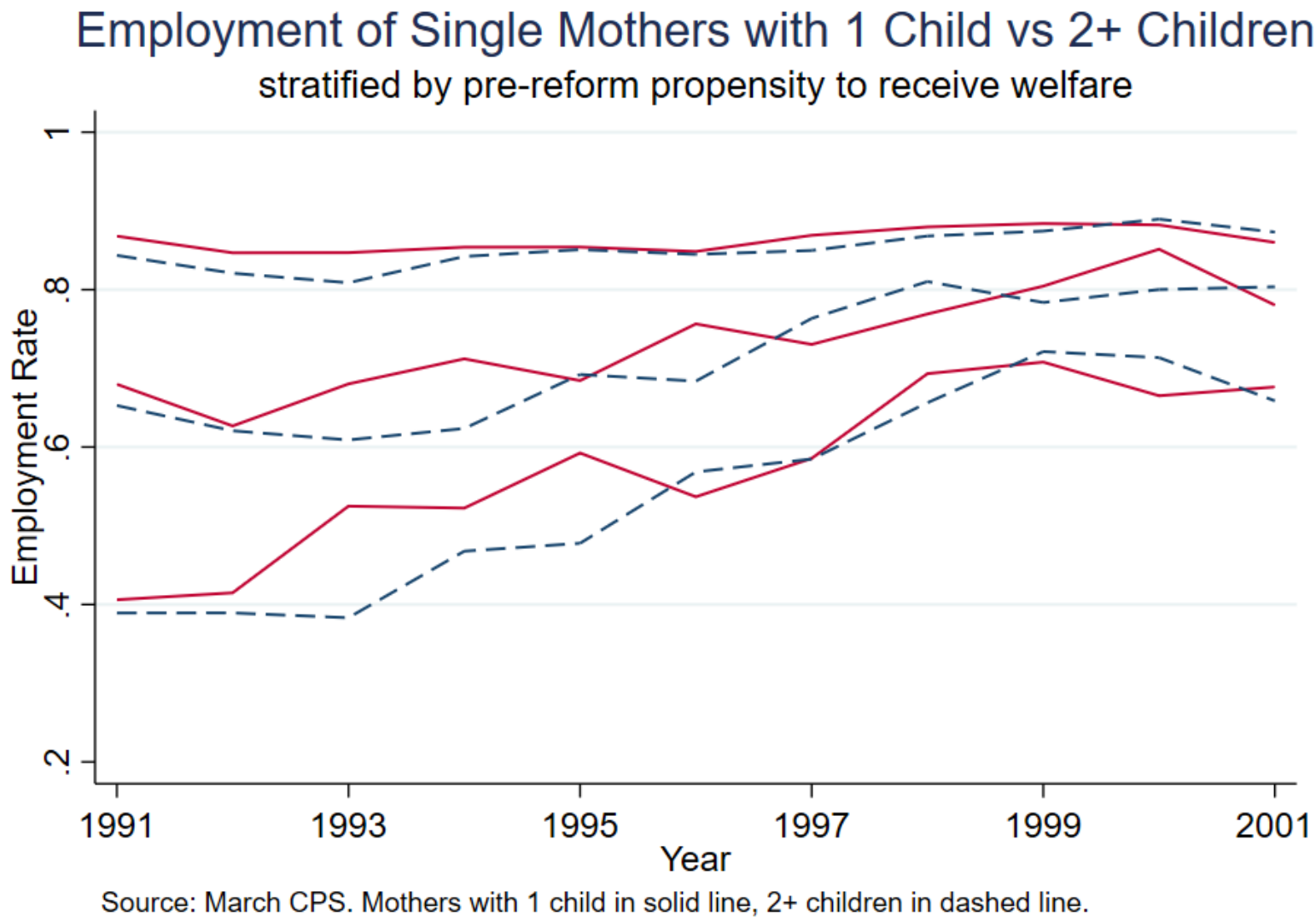
Focus on highest propensity subgroup



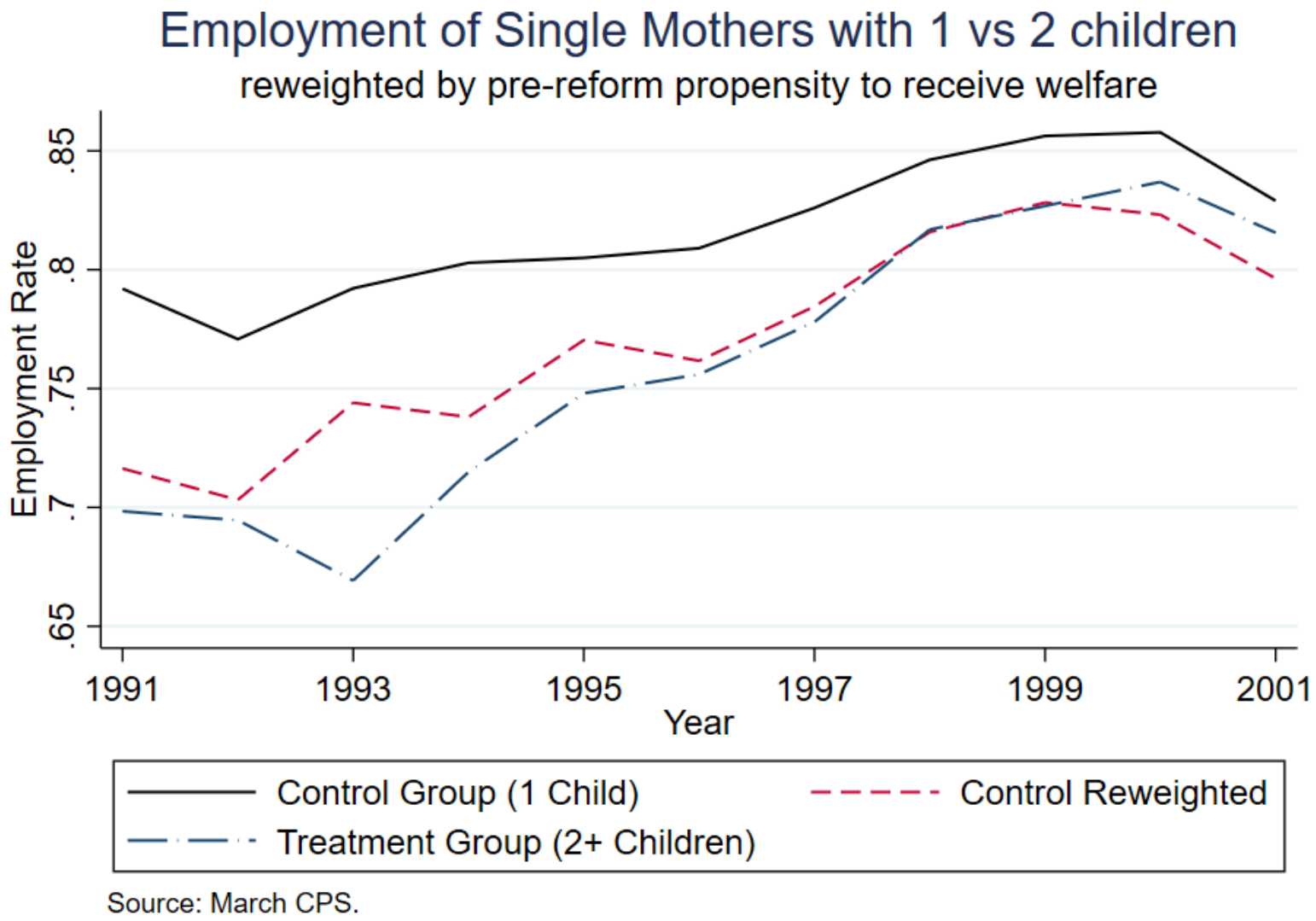
What is within-subgroup treatment effect? Zero.



True for all subgroups



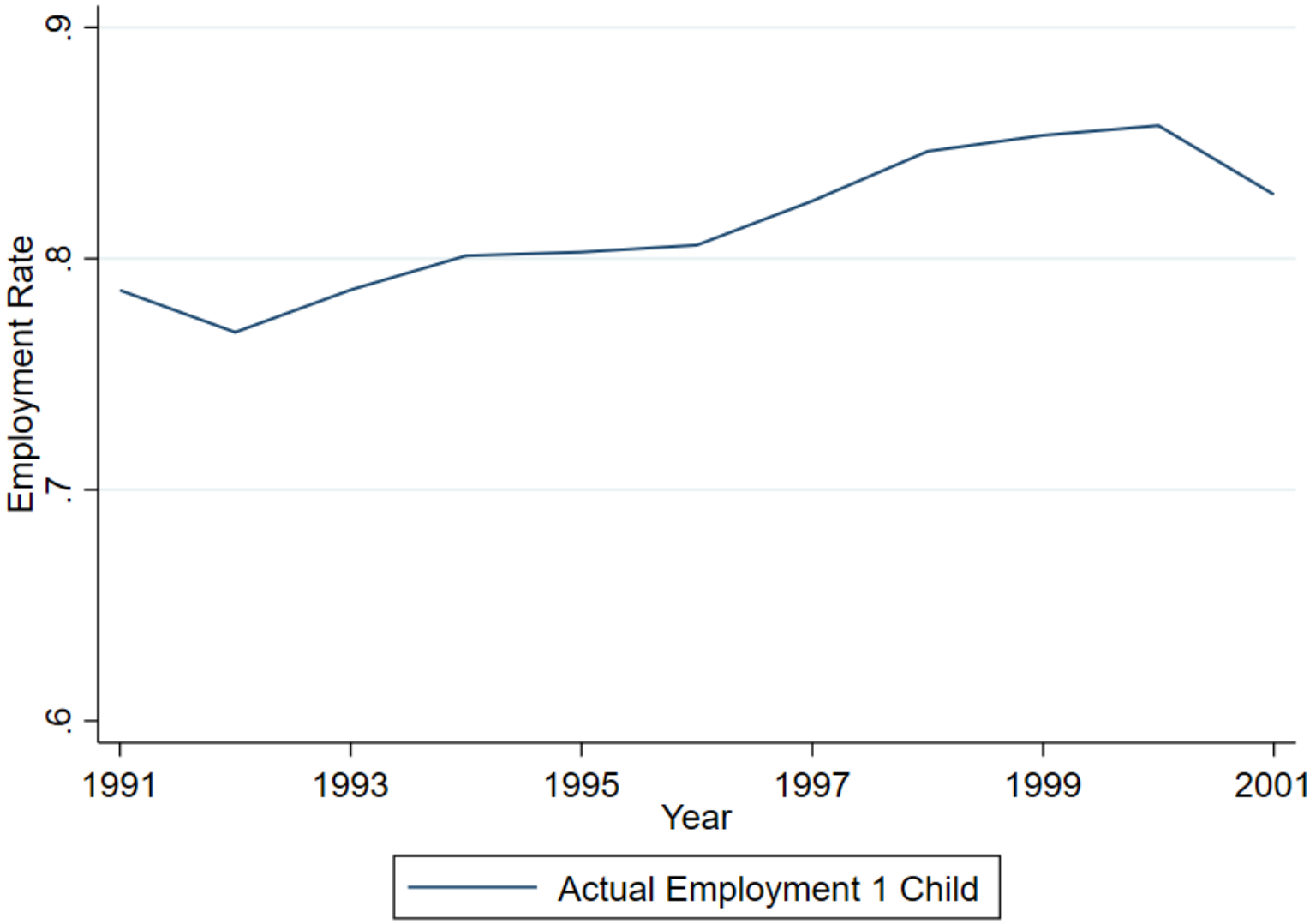
Decomposition shows DiD "explained" by composition bias not treatment effect



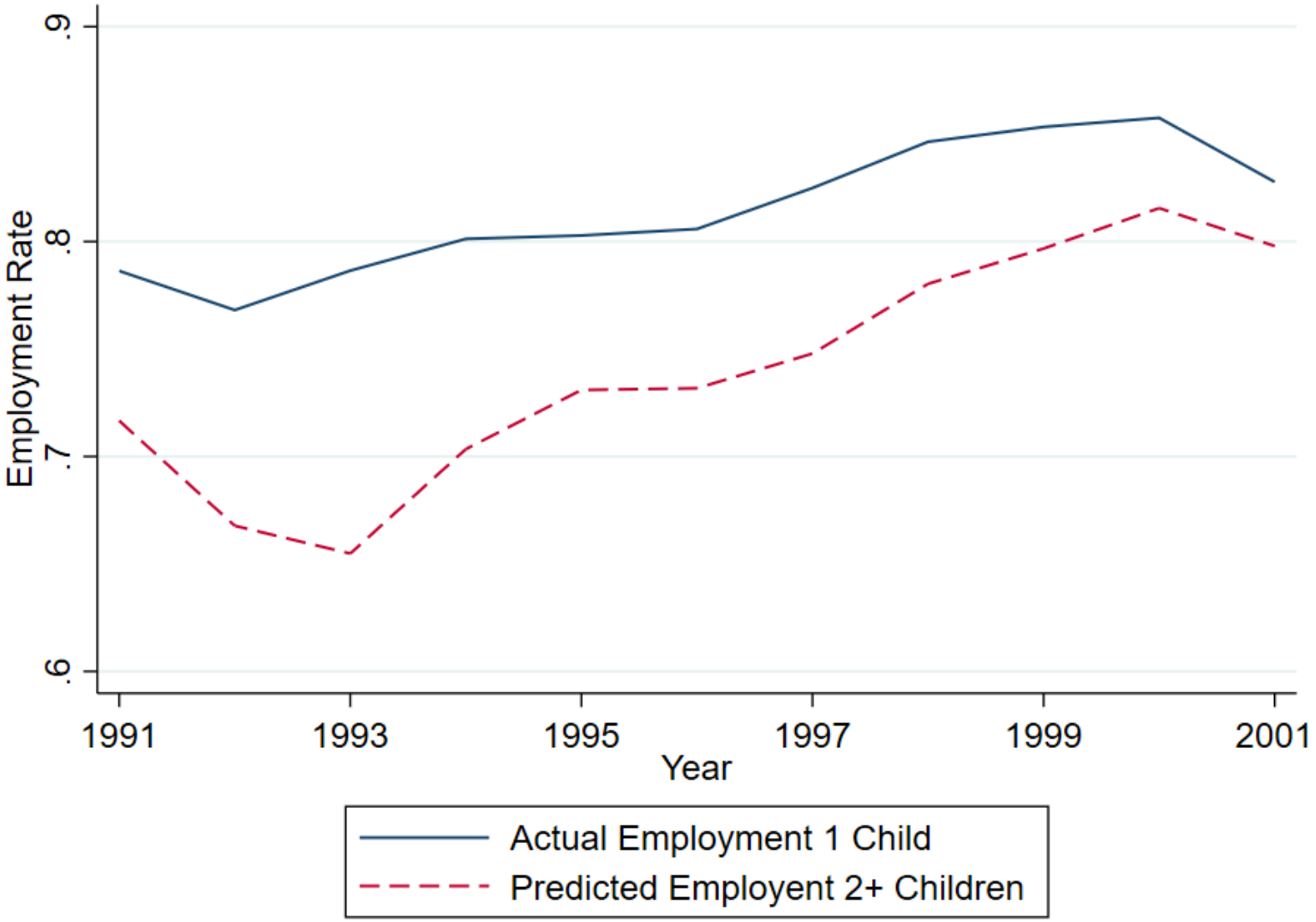
Proactive approach: machine learning

- Off-the-shelf ML for covariate selection
  - Lasso, random forest, etc
- Identify covariates that predict outcome
  - For hypothesis generation
  - And for potential inclusion in main specification
- Train within group and predict across group
  - Visual check: implicitly “assumes” parallel trends

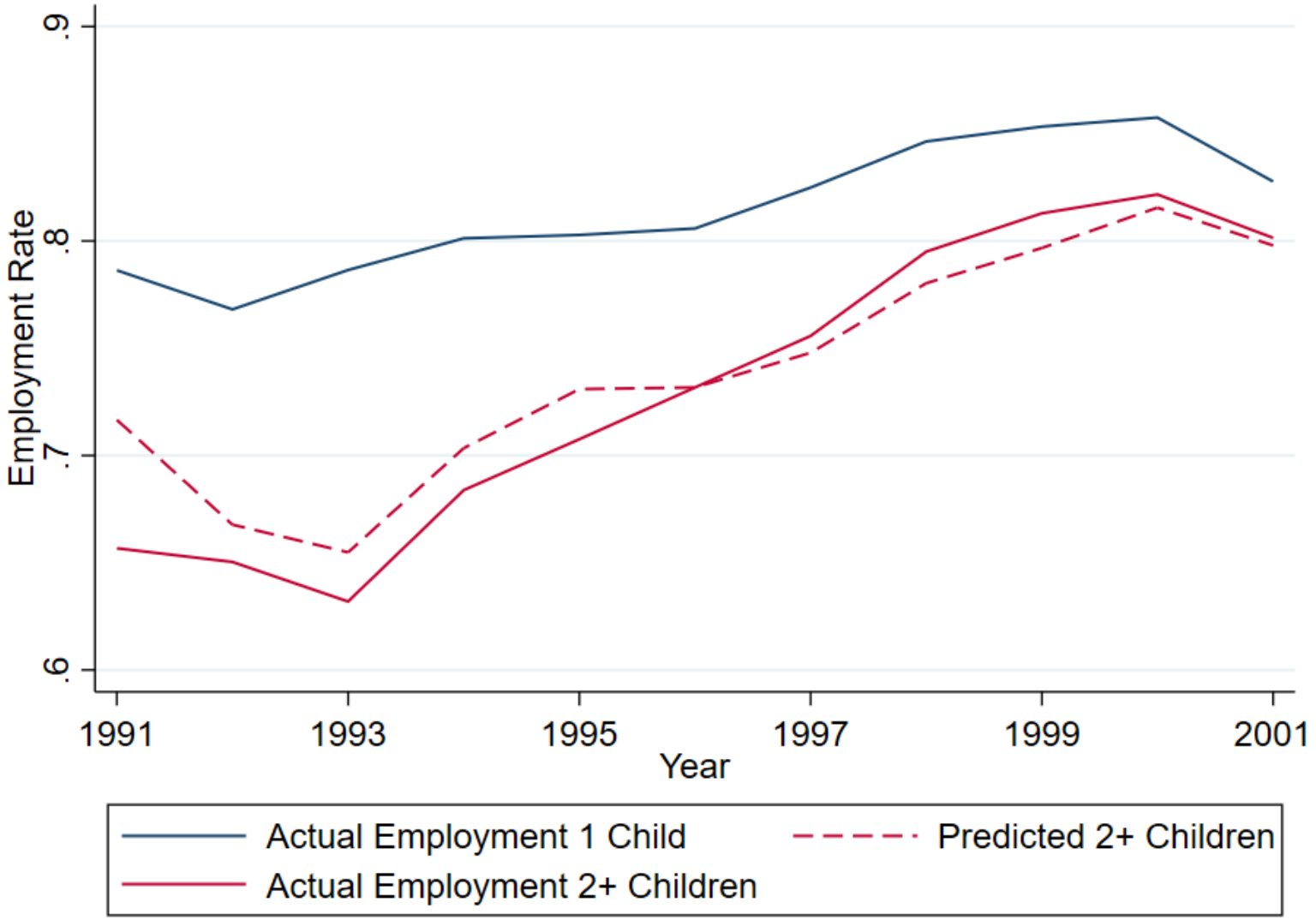
Ex: Train model on control group



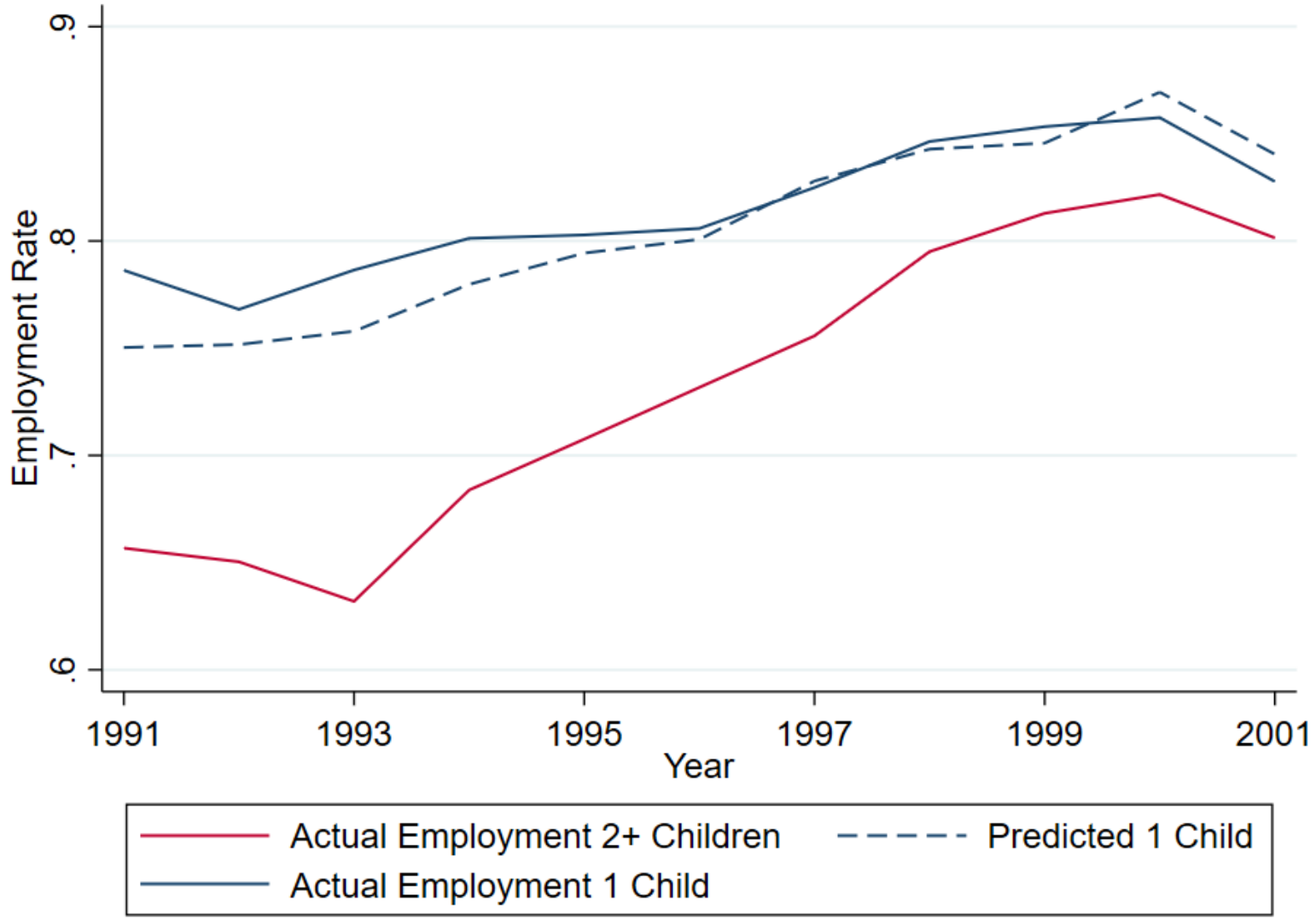
Predict outcome of treatment group. Parallel?



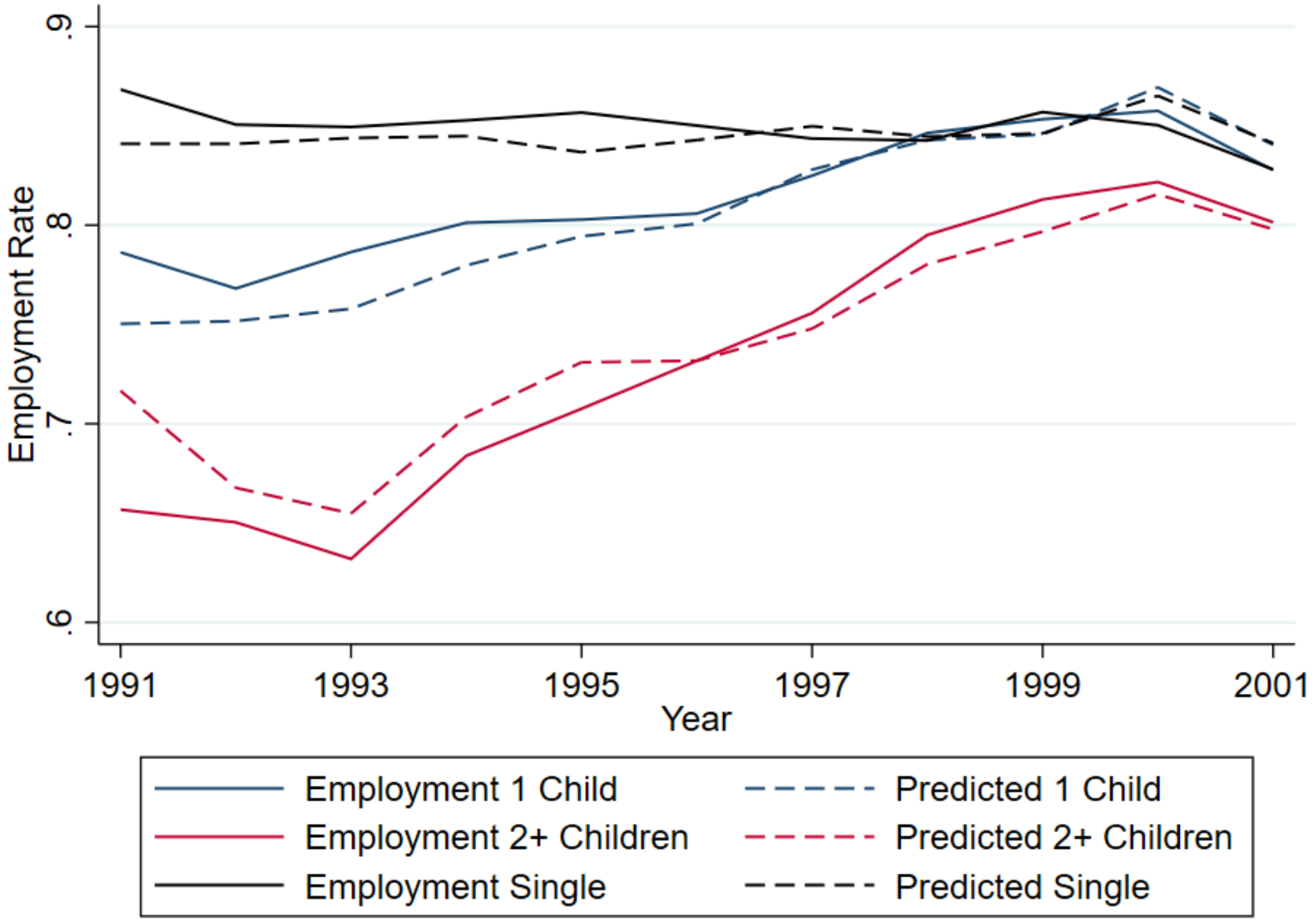
Accurate prediction even in “absence” of treatment effect



Reverse: Accurate despite “including” treatment effect



Visual check on validity of parallel trends assumption



Conclusion

- Canonical DiD estimators of 1993 EITC are confounded by exposure to welfare reform
- Little evidence of EITC's effect on employment in 1990s after controlling for those effects
  - Unclear implications for effect of 1993 EITC on other outcomes
- Sticks, not carrots:
  - Income effects, not substitution effects
  - Implications for economic welfare more negative than believed
- Unconditional transfers reduce labor supply, and sometimes that's ok.

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